

**Interaction and Mechanics:
Understanding Course-Work Engagement in Large Science Lectures**

by

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Table of Contents

Acknowledgements	ii
List of Figures.....	vi
List of Tables	vii
List of Appendices	viii
Abstract.....	ix
Chapter 1: Introduction	1
The Proposed Study	5
Significance of the Study.....	7
Research Questions	8
Chapter 2: Literature Review.....	9
Student Engagement	3
Student Engagement in Higher Education.....	5
Conceptual Framework.....	40
Chapter 3: Research Design	45
Methodology.....	46
Research Context	51
Data Collection.....	54
Measures: Practice Problem Website.....	56
Instructional Observations	66
Data Analysis	67
Contributions.....	81
Chapter 4: Results.....	83
RQ1: The Instructional System	84
Encouraging Course-work Engagement.....	91
Descriptive findings from survey and learning analytics data.....	94
Grade distribution over time.....	102
RQ2A: Stochastic Actor Based (SABM) Results	103
RQ2B: Fixed Linear Effects Model for Course Grade.....	111
Chapter 5: Course-work Engagement in Large Science Lecture Courses	115
Study Design.....	117
Results.....	118
Course-work Engagement in Large Science Lecture Courses.....	123
A new conceptual framework	129
Conclusion	150
Appendices	152
Works Cited	199

List of Figures

Figure 1. Gunuc and Kuzu Course-Work Engagement Model (2014).....	11
Figure 2. How Students Become Engaged in Course-work.....	
in Large Science Lecture Courses.....	43
Figure 3. Aided recall instrument.	58
Figure 4. Data Collection Timeline	67
Figure 5. In-class practice problem from lecture section B.....	87
Figure 6. In-class lecture slide for lecture section C.	88
Figure 7. Course Network	96
Figure 8. In-degree/Out-degree Distribution.....	99
Figure 9. Practice problem attempts by lecture section.	100
Figure 10. Practice Problem User Type by lecture section.....	101
Figure 11. Instructors' academic plans shape course-work engagement.....	125
Figure 12. Space/Time Influences on Course-work Engagement	127
Figure 13. Course-work Engagement in Large Science Lecture Courses.....	130
Figure 14. Socio-matrix for Course Collaboration Network.....	164
Figure 15. Social Ties and Grade by Gender.....	167
Figure 16. Histogram of degrees for observed and random network.....	193
Figure 17. Grade Distribution before each survey by lecture section.....	198

List of Tables

Table 1. Research Questions, Goals, Methods, and Analyses.....	46
Table 2. Instructional activities and assessments varied substantially by class.	52
Table 3. Course Enrollment	53
Table 4. Student Enrollment by Lecture Section.	54
Table 5. Cronbach’s Alpha Consistency.....	59
Table 6. Classroom School Community Index.....	60
Table 7. Expectancy Value Measures for STEM majors	61
Table 8. Additional Questions	62
Table 9. Survey Administration.	65
Table 10. SABM Model Terms	74
Table 11. Structural Network Effects.	75
Table 12. Instructional activities and assessments varied substantially by class.	91
Table 13. Network Census	95
Table 14. Dyad Census	98
Table 15. Practice Problem Classification across time periods.	101
Table 16. Practice Problem Use classification by lecture section	102
Table 17. Structural Network Effects.....	104
Table 18. Social Identity Influences	106
Table 19. Academics and Course Level Influences	106
Table 20. Sense of Community (Affective Academic Beliefs)	107
Table 21. Sender-Receiver Selection Table for Gender (Odds Ratio).....	107
Table 22. Sender-Receiver Selection Table for Citizenship (Odds Ratio).....	108
Table 23. Sender-Receiver Selection Table for Friends (Odds Ratio)	108
Table 24. Practice Problem Website behavioral change.	109
Table 25. Sender-Receiver Influence for Problem Roulette Use (Odds Ratio).....	110
Table 26. Significant Influences on changes in course grade	112
Table 27. Influences on Course-work Engagement in Large Science Lecture	131
Table 28. Course-work Engagement with implications for future research	142
Table 29. SABM Results	161
Table 30. Fixed Linear Model	163
Table 31. Odds of Peer Interaction.....	165
Table 32. Classroom School Community Index Course Form.....	168
Table 33. Classroom School Community Index School Form (from pilot 2)	169
Table 34. Expectancy Value Scale (from pilot 2)	170
Table 35. Odds of Same Gender Ties in the Collaboration Network (Pilot 1-Fall 2014)	193
Table 36. Triad Census (Pilot1- Fall 2014).....	194
Table 37. Observation of Socio-Material Academic Engagement by Class Section.....	197

List of Appendices

Appendix A. Factor Scale Loadings for Expectancy Value Scale.....	153
Appendix B. Factor Scale Loadings for Classroom School Community Index	154
Appendix C. Additional Survey Questions	157
Appendix D. Stochastic Actor Based Model (SABM)	161
Appendix E: Results for Grade Change.....	163
Appendix F. Initial Results from Pilot 1.	164
Appendix G. Initial results from Pilot 2.....	168
Appendix H. Wave 1 Survey Instrument from Pilot 2.....	171
Appendix I. Wave 2 Survey Instrument from Pilot 2	186
Appendix J. ERGM for Pilot 2.....	192
Appendix K: Rate of Change.....	196
Appendix L. Course-work spans socio-material interactions and course space(s)	197
Appendix M. Grade Distribution Figures	198

Abstract

Post-secondary institutions have developed several interventions to address what Chamblis' (2014) calls the arithmetic of classroom engagement. Large lecture courses limit the potential for student/instructor interaction. Instead, large lecture courses have historically relied on an industrialized model of information delivery. Very little is known about how students develop their strategies for completing their course-work in this context.

The aim of this study was to outline a conceptual framework describing how undergraduates become engaged in their course-work in large science lecture courses. Course-work engagement refers to the set of practices that are part of students' efforts to successfully complete a course. Course-work engagement is goal oriented behavior, shaped by the beliefs that individual holds about their self and the course. In the framework, I propose that students' initial beliefs states catalyze their behavioral engagement in the course which is conditioned through feedback from working with peers, from performance assessments, and through interactions with the instructor. This study was conducted in a large (n=551) undergraduate introductory physics course. The course was composed of three lecture sections, each taught by a different instructor.

Based on a review of the literature, I posed the following research questions:

1. What are the relationships among students' peer interactions, their digital instructional technology use, and their performance on assessments in a physics lecture course?
2. How does the instructional system shape students' engagement in peer interactions and their use of digital instructional technologies in a course?

In this study, I employed three methods of data collection. First, I observed instruction in all three sections throughout the semester to characterize similarities and differences among the three lecture sections. Second, I administered two surveys to collect information about students' goals for the course, their expectations for success, their beliefs about the social and academic community in the course, and the names of peers in the course who the student collaborated with in out-of-class study groups. Surveys were administered before the first and final exam in the course. Third, I used learning analytics data from a practice problem website to characterize students' usage of the tool for study preparation before and after the first exam.

Through the stochastic actor based modeling, I identified three salient factors on students' likelihood of participating in out-of-class study groups. First, being underrepresented in the course may have shaped students' opportunities to participate in out-of-class study groups. Women and international students both attempted to participate at higher rates than men and domestic students, respectively. However, women and international students were unlikely to have their relationships reciprocated over the semester. Second, when study tools are incorporated into out-of-class study groups, social influence appears to play a significant role in the formation of course-work engagement. For example, students who were non-users of the practice problem website tended to adopt the use behavior of their higher intensity peers. Third, changes in students' beliefs about the course were significantly related to changes in their course grade.

In terms of performance, students who experienced changes to their course beliefs, or what attempted to form new out of class study groups in the lead up to the third exam, were likely to experience academic difficulty. This study highlights the important role of time and the dynamic role of social interaction on the development of course-work engagement in large science lecture courses.

Chapter 1: Introduction

Institutions of higher education have, for most of their existence, attempted to address the challenge of what Chambliss (2014) calls the arithmetic of engagement. With limited spatial, temporal, and human resources to provide instruction, college instructors and administrators often must make tradeoffs between low student/teacher ratios and high costs. The large lecture hall, where hundreds of students are provided instruction simultaneously, is one attempt to solve this equation. Institutions make a large investment in space and reap economies of scale by delivering information to many learners simultaneously. Some evidence suggests that students make equal learning gains in small and large courses (Glass & Smith, 1979; Johnson 2010; Williams, Cook, Quinn, & Jensen, 1985), but these studies do not address the extent to which the work of learning is distributed across the rest of the classroom learning community, with students' academic centered peer interactions or their use of instructional technologies replacing interactions with the instructor.

A major limitation of the large lecture hall is reduced interaction between teacher and student. With upwards of 200 students, instructors cannot realistically engage and direct each student in the learning process. This lack of interaction potentially results in a generalized model of instruction that is not responsive to the individual needs of learners. In a small classroom, teaching and learning activities could be structured or even adjusted on the fly to be more responsive to the needs of individuals. Instead, in large lecture halls the learning process might be distributed across instructional materials, digital instructional technology, and among peers enrolled in the course.

The lack of student/teacher interaction is especially problematic in undergraduate science courses where students often benefit from interactive learning. For example, in a review of 64

different introductory physics courses at the high school and undergraduate level, Hake (1998) observed that students in interactive physics courses made substantial gains, on average, in comprehension of mechanics concepts over students in traditional lecture classes. Interactive instruction where peers solve problems collaboratively consistently leads to performance gains in large physics lecture halls (Mazur, 2009). The of a network of students in a course, is one potential resource that instructors can harness to improve student academic performance.

As a result, instructors, curriculum developers, and educational technologists have developed several interventions designed to engage students in the learning process in large lecture hall courses, where the use of different types of course learning resources are encouraged. In a typical undergraduate science lecture course, students have access to an array of potential learning resources. Students may draw on their peers in a class to help them make sense of a confusing concept (e.g. Ge & Land, 2003; Mazur 2009), or they might engage with online help tools created by the instructor to test their knowledge. According to one study conducted at the University of Michigan (UM), undergraduate students had over 80 learning resources available to them that spanned the undergraduate curriculum, including face-to-face tutoring, study groups, and web-enabled technologies (Makara & Karabenick, 2013). Many of these resources, such as supplemental instruction (Blanc, DeBuhr, & Martin, 1983) and help room hours, are designed with specific courses and course content in mind. Given the wide array of options, students make individual choices about whether to work with some peers in the classroom and/or adopt and use different technologies.

Students in large lecture courses need not rely on any one resource to support their learning, and the abundance of possible learning resources suggests that students need to develop purposeful strategies for navigating the multitude of options available to them. Yet, how students develop resource selection strategies in large lecture halls is not well understood. Research that investigates

how students develop and refine their resource use strategies is needed, as institutions seem to be increasingly interested in pursuing efforts to develop instructional material, technology, and practices that facilitate personalized learning (e.g. Moyer, 2015; Next Gen Learning Challenge, 2014).

Instructors and institutions that aim to facilitate personalized learning in large courses have pursued two concurrent intervention strategies. One approach to teaching in large lecture courses involves using student-centered instruction to promote interaction and sense-making among learners in large courses where student/instructor interactions are rare. This approach is often predicated on the logic that 1) students benefit equally from this approach and 2) students have equal opportunity to participate in and develop the relationships that support peer study partnerships. However, very little research examines how out-of-class study groups form and what impact they might have on students' performance in a course.

A second approach involves developing digital instructional technologies (DITs), delivered through the internet, that provide students the opportunity to review course material and provide users some sort of feedback about their current understanding of course material. Digital instructional technologies are increasingly pervasive in undergraduate instruction, such that some scholars have predicted that teaching with DITs will become "the new traditional model" (Ross & Gage, 2006, p. 168; Norberg, Dziuban, & Moskal, 2011; Watson, 2008). As of 2010, about 60% of students in American undergraduate higher education had received instruction with DITs (Radford, 2011). A more recent survey of undergraduate instructors reports that nearly half used DITs as part of their instructional practice (Eagan, Stolzenberg, Berdan Lozano, Aragon, Ramirez Suchard, & Hurtado, 2014). In order to facilitate personalized learning, educators need an understanding of the impact of digital instructional technologies as well as the impact of collaborating within the classroom learning community.

Understanding these two learning resources (community and technology) is essential because classroom learning rarely happens in isolation (Kumpulainen & Wray, 2002). In-classrooms, students, instructors, and instructional technologies are part of a “goal oriented and artifact mediated” (Leontiev, 1981) social system. Instructional activities, instructional moves, and assessments can all influence students’ decision making. The choices that students make about the learning resources that they use in their course-work (which mediating artifacts they employ and which interactions they engage in) can make the difference between academic success and failure.

Many scholars in higher education have investigated the impact of instructional strategies on student outcomes, such that some consensus approaches are widely applied. Active engagement strategies (Freeman et al., 2014; Prince 2004), the use of instructional technologies (Bernard, Borokhovski, Schmid, Tamim, & Abrami, 2014), and peer interaction during instruction (Crouch & Mazur, 2001; Mazur 2009) are common approaches to encouraging the engagement of learners with course-work. However, investigations of each approach generally focus on the intervention in isolation from other instructional practices and tools (Gašević, Dawson, Rogers, & Gasevic, 2016). Some studies of active learning account for the role of instructional technology such as clicker systems (Blasco-Arcas, Buil, Hernández-Ortega, & Sese, 2013; Crouch & Mazur, 2001), but in those studies instructional technologies are usually investigated in the context of their classroom use as configured by the instructor. How students might make use of other instructional technologies like smart tutors and online practice problem generators that are also course-based learning resources are generally ignored if they are not part of the in-class instructional strategy.

Alternatively, when mediating technology is the focus of the study, classroom instructional practices are often glossed over. That students might choose between the learning resources that extend from each approach -- that is, that students might choose some constellation of peer interaction and digital instructional technologies -- is given little consideration outside of the work of

socio-material scholars like Jan Nesper (2011), Richards Edwards (2012), or Tara Fenwick (2009). In socio-material educational research much attention is paid to what students and instructors are doing, but the impact of the illustrated behavior of students and instructors on students' outcomes is not addressed. In short, researchers rarely examine the relationship between engagement in the course peer network, instructional technology use, and student outcomes in large lecture courses.

The Proposed Study

The study described in the following chapters examines the relationships among students' engagement in a network of peers enrolled in the course, students' use of instructional technologies, and their academic performance in an undergraduate introductory physics course. Introductory physics is a gateway course to many scientific and technical majors in higher education (e.g., engineering, material science, astrophysics), and scholars argue that to be academically successful in physics major programs students must adopt a "logic of collaboration" (Nesper, 1994, p. 101). Research indicates that students' academic performances in physics courses are linked to their academic collaborations with peers, such that students who work in isolation are less likely to be successful in physics courses (e.g. Forsman, Moll, & Linder, 2014; Mazur 2009).

Physics instructors have also developed a wide array of instructional technologies for use in introductory course-work, like learning management systems, smart tutors, digital textbooks and homework systems, and audience response systems (Docktor & Mestre, 2014). In fact, at the University of Michigan, physics instructors have developed an online, practice- problem mobile application (Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013) that is particularly popular in physics courses. The effectiveness of these technologies for improving student academic performance is an unresolved question, in part, because they are so new and, in part, because scholars have not explored their use alongside other traditional strategies like out-of-class study groups.

In this study, I propose to use data about students' peer interactions and use of digital instructional technologies, as well as observations of instruction, to develop a holistic model of factors influencing students' use of course-based learning resources. I focus on a large lecture course because in that context instructors are more likely to adopt technologies that support personalized learning (like digital instructional technologies) and students' course resource use can too often become invisible to instructors; large lecture courses also offer a complex context with sufficiently large samples for quantitative analyses. Students become one of many trees in the forest of a lecture hall, sharing a variety of resources but thriving seemingly of their own accord. This research will retrain our attention to the ecosystem of the classroom learning community.

For the purposes of this study, "digital learning resources" refer to instructional technologies like digital textbooks, course websites, and online homework systems; the impact of which researchers have begun to explore in earnest (Papamitsiou & Economides, 2014). In this study, I also focus on students out-of-class study groups as a study resource because of the paucity of research on students' academic-centered interactions with their classroom peers in out-of-class contexts (e.g. Callahan, 2008). Students' interactions potentially take on increased importance in large lecture courses because peer-to-peer interactions may be the only opportunity for students to engage in the co-construction of meaning around course topics. By studying the interactions among peers and between students and instructional technologies, I aim to shed light on important forces that shape individual learning in large courses. Through observations of teaching activities, I also hope to identify instructional moves that foster (or deter) the emergence of peer connections alongside students' individual learning resource use strategies. Studying the interdependent influence of the social ties that structure peer interactions in concert with a student's learning technology usage could provide important insights into the array of social and technological learning resources that students assemble to support their academic performance. For example, we might finally be

able to differentiate the influence of digital learning resource use and the tendency towards engagement with peers as complementary and/or divergent approaches that influence variations in academic outcomes. To date, conceptual models for studies of student learning technology use reflect the division between research on technology and social learning in which one approach or the other is adopted and refined. I hope to offer a more expansive model of socio-technical resource strategy development that suggests new directions for investigation, instructional practice, and instructional tool development as well as potential learning analytics applications.

Significance of the Study

Until recently, studies of the sort I propose were hampered by a lack of cost-effective tools for data collection and appropriate tools for analyzing the influence of peer relationships on student outcomes (Biancani & McFarland, 2013). This left unresolved the question of how collaborating with student A influenced student B's engagement and learning. Researchers could assert, but not demonstrate, that students who collaborated outperformed those who were isolated (Brunello, De Paola, & Scoppa, 2010; Carrell, Fullerton, & West, 2008; Foster 2006).

Two significant changes have made the study of peer interaction and digital technology use more manageable and affordable. First, learning management systems (LMS) have created an automated system for capturing data about students' use of digital instructional technology like digital textbooks and online homework systems (Krumm, Waddington, Lonn, & Teasley, 2012). Shum and Ferguson (2012) argue that the utility of this kind of big data analysis, what is frequently termed learning analytics, would be expanded significantly by the incorporation of peer interaction data.

Second, advances in the statistical modeling of networks allow scholars to consider the influence of peer collaborations on student outcomes (Snijders, Van de Bunt, & Steglich, 2010) by modeling both 1) the influence of collaboration between high and low performing peers in the

course as well as 2) the configuration of a network of collaborators on students' outcomes (Dishion, 2013). This approach would also extend our understanding of how to build models for personalized learning that capitalize on the affordances of digital instructional technologies and peer interactions.

Research Questions

This study seeks to identify the impact that students' choices among participation in students' out-of-class study groups and use of instructional technology to prepare for the course may have on their academic performance. The following research questions guide the research:

1. How does the instructional system shape students' engagement in peer interactions and their use of technological tools in a large lecture course?
2. What are the relationships among students' peer interactions, their instructional technology use, and their academic performance?

The results of this project offer important insights into the process of how students develop strategies for selecting and using learning resources, highlighting future directions for the development of practices and technologies that support personalized learning in large lecture courses. In the next chapter, I review the literature on student engagement, academic centered peer interactions and digital instructional technology use, and introduce the conceptual model that will guide the study.

Chapter 2: Literature Review

Three approaches to studying students' outcomes in a course are common in the literature on post-secondary education (Kahu, 2013). First, factors that predict persistence by students, such as social influence, social engagement, academic engagement and institutional contextual influences are investigated (Robbins, Lauver, Le, Davis, Langley, & Carlstrom, 2004). Second, motivation researchers examine students' goal and expectations for success to understand the time and energy they invest in their academic performance (Robbins et al., 2004). Finally, researchers interested in the scholarship of teaching and learning have focused on how instructional strategies might promote student course resource use (e.g. Buchwitz et al., 2012; Prince 2004). Research that sits at the intersection of these three approaches could shed light on student behavior as shaped by instructional strategies and the learning community in a course.

There is growing consensus on the need to combine these three perspectives, and this chapter responds to that need for a new conceptualization of student course engagement that can guide research in this area. With this aim, I first review literature focused on the primary influences on students' resource use, beginning with an overview of research on student engagement and course engagement in higher education to identify the salient constructs that shape students' investment of time and energy into different course resources. Next, I review the literature on instructional practice as it relates to students' use of social and technological resources. Using a framework for studying engagement in post-secondary education developed by Kahu (2013), I offer some insight into how cognitive factors like motivation and affective factors like classroom sense of community might inform resource use. Finally, I review and critique the literature on two types of

course resources-- digital instructional technology and academic centered peer interactions—to illustrate their role in behavioral engagement and to clarify the relationship of these resources to academic performance. I close this chapter with my proposed conceptualization of student course engagement as a dynamic process shaped by interaction among peers enrolled in a course and between students and instructional technologies.

Student Engagement

The research on student engagement provides one way of thinking about course resource use, in which use is understood as a form of investment in a learning strategy. Recognizing the entwinement of behavior, cognition, and affect, Astin (1984) defined engagement as “the amount of physical and psychological energy that the student devotes to the academic experience” (p. 284). Kuh (2013) offered a definition for student engagement in higher education, suggesting engagement involves,

the time and energy students devote to educationally sound activities inside and outside of the classroom, and the policies and practices that institutions use to induce students to take part in these activities (p. 25).

Within formal educational environments, where curriculum, programs, and instruction are intentionally designed, engagement involves making choices among the programs and resources offered by a school (Natriello, 1984, p. 14). The interest in engagement stems in part from the assumption that students’ investment of time and energy are malleable (Fredricks, Blumenfeld, & Paris, 2004). Engagement results from individuals interacting in learning environments where variations in engagement are a function of variation in the environment and of student perceptions of the course (Connell, 1990; Finn & Rock, 1997; Fredricks et al., 2004). Engagement is shaped by influences at the individual, organizational/classroom, and institutional levels. It is ongoing, it is iterative, and it changes over time because of changes to tasks and contexts. As such, engagement is a process in addition to being an outcome of students’ interactions.

The wide interest in undergraduate student engagement as a behavior that can be modified has resulted in a diverse approach to its conceptualization, with various components identified as essential to the construct (Mandernach 2015). As a research base, student engagement draws from sociology, psychology, organizational theory, cultural anthropology, as well as pedagogic and social network perspectives (Kuh, et al., 2006). Many scholars of education have suggested that student engagement is a meta-construct, under the tent of which scholars might explore aspects of motivation, sense of belonging, and socialization to school (Fredricks, Blumenfeld, & Paris 2004; Appleton 2012). Under that broad umbrella, foundational student engagement studies in higher education explored academic behaviors like time on task (Merwin, 1969), quality of effort (Pace, 1982), academic and social integration (Tinto, 1987, 1997), and “good” practices in undergraduate education (Chickering & Gamson, 1987).

In a landmark review of the research literature on school engagement, Fredricks et al. (2004) identified three primary aspects of student engagement: behavioral, cognitive, and emotional engagement. Although their research review focused on K-12 schooling, the constructs they identified are easily portable to other formal instructional contexts. Each aspect of engagement speaks to a set of influences and experiences that shape the investments students make in schooling. Cognitive engagement represents a student’s willingness to “exert the effort necessary to comprehend complex ideas and master difficult skills” (Fredricks et al., 2004, p. 60). Emotional engagement is based on the “positive and negative reactions to teachers, classmates, academics” and campus culture (p. 60). Emotional engagement can influence a student’s sense of community on campus and her willingness to invest time and energy in schooling. Behavioral engagement refers to students’ involvement in the activities of learning in a course. This includes interaction with course material and interaction with peers. Prior research suggests that students’ time on task (Brophy, 1983; Fisher, Berliner, Filby, Marliave, Cahen & Dishaw, 1980; McIntyre, Copenhaver, Byrd, &

Norris, 1983; Merwin, 1969), their outside of the classroom responsibilities (Masui, Broeckmans, Doumen, Groenen, & Molenberghs, 2012; Svanum & Bigatti, 2006) and their engagement in peer interaction (Chambliss 2014) all have a potential impact on student engagement (and subsequently on their academic performance).

Student Engagement in Higher Education. Narrowing the focus to research on student engagement in higher education, three theoretical traditions are dominant: the behavioral, the psychological, and the socio-cultural (Kahu, 2013). Research within each of these traditions conceptualizes post-secondary student engagement in ways that privilege one aspect of student engagement over the others.

The behavioral perspective, which attends to the role of effective instructional and institutional practice (Kahu, 2013), is the popular approach among higher education researchers and practitioners. Building on the seven principles of good practice in undergraduate education identified by Chickering and Gamson (1987), the behavioral perspective trains researchers' attention to the "time and effort students devote to educationally purposeful activities" (Australian Council for Education Research, 2010, p. 1). By focusing on observable and externalized behavior, instructors and institutions can develop interventions that respond to (and seek to shape) student behavior. For example, the behavioral perspective requires observations of behavioral engagement to measure cognitive engagement. Most research on digital instructional technology use belongs firmly to the behavioral perspective (e.g. Papamitsiou & Economides, 2014).

The alternative perspectives address important and salient aspects of learning and development. The psychological perspective, in contrast to the behavioral, focuses on internal individual processes. Students' responses to active learning, for example, and their motivation to complete course-work are aspects of cognition explored in the psychological research (Richardson, Abraham, & Bond, 2012). This work frequently overlaps with studies of student motivation and self-

regulation (Appleton, 2012) to such an extent that the conceptual boundaries between motivation, self-regulation, and student engagement are difficult to parse. Studies of emotional well-being and its relationship to engagement are also common in this perspective, presumably after the influential work of Tinto (1987) who observed that social and emotional well-being were linked to engagement. Academic motivation (Pintrich, Marx, & Boyle, 1993) and affective beliefs about campus life (Strayhorn, 2012) in a course are generally explored from the psychological perspective.

The socio-cultural perspective on student engagement in higher education focuses on the political and social dimensions of schooling. Studies of campus environments and organizational pathways reflect the role of the political economy in shaping students' engagement on campus. For example, Armstrong and Hamilton's (2013) *Paying for the Party* examines the campus experiences of low-income and wealthy undergraduate women, and how their pathways towards graduation and their campus engagements are shaped by their social class and the organization of the co-curriculum.

Kahu (2013) attempts to pull together these three perspectives by situating the ongoing process of engagement in the socio-cultural context of post-secondary schooling. Structural influences on the level of the individual and the institution inform psychosocial influences where relationships and internal beliefs are fostered (Kahu, 2013). This set of influences are mutually constitutive as part of student engagement, which is comprised of affect, cognition, and behavior. Engagement results in immediate and long-term consequences comprised of academic and social outcomes.

Kahu illustrates this framework with earlier work on student engagement, like Llorens, Schaufeli, Bakker, and Salanova's (2007) finding that engagement breeds engagement. In that study, learners who believed they had sufficient resources to be successful in a course experienced increases in self-efficacy during the course, which in turn informed their engagement, which then

increased their self-efficacy. Additionally, as Kahu noted “engagement leads to better grades, which in turn motivate students to be more engaged” (p. 760).

Kahu’s framework, although comprehensive, does not situate specific forms of engagement in their context. That task is left up to the researcher, who makes decisions about which relationships to focus on, what internal factors like motivation to focus on, and what outcomes to measure. As Kahu notes,

No single research project can possibly examine all facets of this complex construct. But, by starting from a place that acknowledges the multi-level phenomena and processes, and the complex relations between them, the focus can be on developing a greater understanding of one element without denying the existence of the others. (2013, p.770)

As such, an agenda for research on use of course resources could focus on the factors within the framework that are salient. Motivation, relationships, student backgrounds, and the structural influence of the institution all inform how students make investments in different course resources. Research is needed that treats engagement as multifaceted and explores how “attempts to alter context influence all three types of engagement determining whether outcomes are mediated by changes in one or more components” (Fredricks et al., 2004, p. 61).

Course-work and Student Engagement. Undergraduate student engagement is typically investigated at the institutional level, asking students about their engagement in their courses generally. A few scholars, however, have developed measures of engagement in courses, approaching course engagement either as the phenomenon of interest or as a variable in studies of student motivation or self-regulation. In a review of scales for measuring students’ engagement in course-work, Zabel and Heger (2015) distinguished between macro-level measures focused on the campus environment and micro-level measures of students’ behaviors in classroom environments. The authors observed that “a dearth of research has examined the measurement of student engagement as it pertains to classroom material” (p. 88). In this section, I review the three most

widely cited conceptualizations of engagement found in the empirical literature, their commonalities, and their strengths and limitations. Although each approach holds value and promise, each also suffers from significant limitations that recommend the development of a new approach reflective of the framework proposed by Kahu (2013) and the dimensions of engagement popularized by Fredrick et al. (2004).

Perhaps the best-known measure of student engagement is the National Survey of Student Engagement (NSSE, 2002), which takes a macro approach to examining students' experiences across the institution. While respondents are asked about their in-class and in-course experiences, they are asked to report their level of engagement across courses rather than for individual courses. Engagement in this conceptualization is one aspect of a broad portrait of institutional effectiveness. The NSSE also lack a "rigorous theoretical orientation that drives the organization" of its items (Zabel & Heger, 2015, p. 89). Additionally, Porter argued (2011) that the NSSE fails to meet basic standards of reliability and validity in survey design.

As an alternative to the NSSE, some scholars have focused on conceptualizing course engagement as a distinct phenomenon from student engagement. The Student Course Engagement Questionnaire (SCEQ) is the most widely used measure that focuses on course-work explicitly and has been empirically validated in a number of course environments (Henrie, Halverson, & Graham, 2015). The SCEQ asks students to report what happens within and immediately before and after class time (Handlesman, Briggs, Sullivan, and Trowler, 2005, p. 185). The instrument contains four subscales that focus on skills engagement, peer/interaction engagement, emotional engagement, and performance engagement. The four subscales were identified through factor analysis of items generated by the authors based on a review of the student engagement literature. Although the focus of the SCEQ is on post-secondary contexts, the literature that the authors draw from focuses primarily on K-12 education (Handlesman, et al., 2005).

The SCEQ resembles, but does not adopt, the dimensions of student engagement identified by Fredricks et al. (2004). Skills engagement consists of nine items that represent “engagement through practicing skills” like taking and reviewing class notes (p. 186). This scale is similar to behavioral engagement in its focus on externalized material practices (e.g., completing homework and course readings; taking notes; attending class).

Emotional engagement is composed of five items and represents engagement through students’ emotional reactions to course material. Students are queried about their ability to apply what they have learned to their life and their desire to learn the course material. This conceptualization of emotional engagement differs from Friedrich and Kahu’s conceptions in that emotions are bounded to the classroom and generally relate to the curriculum and not interactions with peers or instructors.

Instead, peers and instructors are accounted for in the interaction and participation subscale. Composed of six items, this subscale asks about students’ tendency to participate (e.g., raising a hand to ask a question, having fun in-class, working in small groups) and interacting with the instructor by attending office hours. Here interaction is bounded to the classroom environment and academic-centered interactions with the instructor outside of class time.

The final scale, performance engagement, echoes skills engagement through its focus on embodied material practices. Performance engagement also draws from the literature on performance orientation, which describes an approach used by students who are focused on improving their metrics from assessments; performance orientation is contrasted with a mastery orientation in which students seek deep learning of the material. This focus on performance engagement is odd, in part, because instructors generally hope to inspire students towards mastery orientations in lieu of performance orientations (e.g. Chickering & Gamson, 1987).

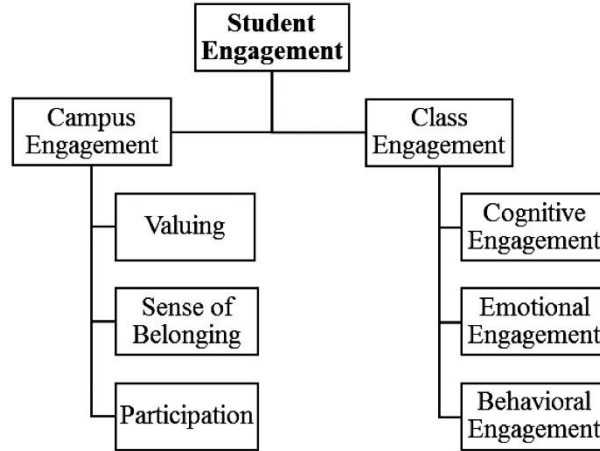
It seems likely that, given the difficulty in measuring deep learning specifically or cognitive engagement generally, researchers turned to easily observable (or reportable) behaviors. The SCEQ conceptualization of engagement also intermingles internal and external processes, in part, because the items in the factor scales are not grounded in a theoretical perspective (Zabel & Heger, 2015). For example, note-taking is considered an academic skill in the SCEQ while raising a hand in the classroom to ask a clarifying question is evidence of participation and interaction. Yet, both contribute to conceptual understanding of the material, require processing, and both are externalized behaviors that indicate some level of engagement and participation in the classroom.

As the researchers do not clarify what framework guided the development of the SCEQ, the authors have produced a model that while effective at predicting course grade (Handelsman, Briggs, Sullivan, & Towler, 2005b; Henrie et al., 2015) provides little insight into how the individual behaviors they are interested in relate to each other. For example, participation in the classroom and interactions with the instructor are collapsed into one scale, but how are these two practices similar and dissimilar and how do they relate to each other? What larger construct do they represent? The focus on what happens immediately surrounding class also divorces course engagement from the larger campus context that shapes student engagement. The relationship between undergraduate student engagement and course engagement is ignored, if not outright discounted.

In contrast to the macro focus of the NSSE and the micro focus of the SCEQ scale, Gunuc and Kuzu (2014) proposed a theoretical model of student engagement that includes both campus and classroom engagement. As displayed in Figure 1, campus engagement is comprised of participation, sense of belonging, and valuing. Participation focuses specifically on active involvement in campus or out-of-class activities and programs. Students with a high sense of belonging feel embraced by other students, faculty and staff on campus. Although they include it in their model, the authors do not offer a specific definition of valuing, and they frequently conflate

valuing and sense of belonging without clarifying what either encompasses (e.g. psychological engagement, affective beliefs).

Figure 1. Gunuc and Kuzu Course-Work Engagement Model (2014)



Gunuc and Kuzu draw upon on Fredricks et al. (2004) to define class engagement, which is composed of cognitive, behavioral, and affective dimensions. Cognitive engagement encompasses “investment on learning, valuing learning, learning motivation, learning goals, self-regulation and planning” (p. 590). Behavioral engagement includes attendance, participation, and out-of-class involvement in course-work. Emotional engagement refers to “students’ emotional reactions -- including their attitudes, interests, relationships and values -- to the teacher/staff, peers, course content and class” (p. 590). Factor analysis revealed that interactions with peers and interactions with faculty members were separate but related constructs within emotional engagement, although why these interactions constitute emotional engagement as opposed to behavioral engagement is not addressed. In this way, Gunuc and Kuzu commingle externalized behavior with internal belief structures just as the authors of the SCEQ. Despite their use of factor analysis, the latent constructs that each scale represents do not seem sufficiently independent in their current conceptualizations to draw clear boundaries.

The primary strength of the Gunuc & Kuzu model is that it affords students the opportunity to register their engagement as well as their disengagement —something the NSSE and SCEQ

surveys do not allow. The authors also make clear the prior research that generated each item on the survey. The survey is comprised of 54 items, most of which focus on campus engagement instead of classroom engagement. Thus, while the model and instrument do a good job of situating students' affective reactions to class-work in their larger sense of belonging on campus, the data collected cannot reveal much about the inner workings of a course.

The NSSE, CSEQ and Gunuc & Kuzu measures largely sidestep the complexity of the instructional environment in attempting to unpack students' course engagement. None of these approaches seeks to identify how different instructional strategies might shape engagement in course-work. Although Zabel & Heger (2015) argue that the course engagement scales they review traverse the micro level of student behavior and the macro levels of campus wide undergraduate student engagement, I would argue that no scale effectively captures the meso-level of the course for the following reasons.

First, all the measures of behavioral engagement rely on retrospective reporting despite the wide abundance of usage and trace data that could provide direct measures of student behaviors. Direct measures of behavioral engagement would offer a superior metric for operationalizing what students do in the classroom, as survey measures and retrospective reporting are one abstraction removed from students' real practices. Second, these measures underestimate the influence of social learning, by either focusing on the broad campus environment or by glossing over the ways that students interact before, during, and after a course around course-work. Although all three approaches ask questions about peers—and the Gunuc and Kuzu scale identifies peer interactions as a distinct construct that influences engagement—none of the instruments ask direct questions about peer interactions.

Perhaps most glaring, no approach attempts to conceptualize the role of the peers enrolled in the course. Community in the NSSE model of engagement is defined through participation in

campus life, with classroom engagement one aspect of the larger construct. The SCEQ fails to theorize how peers might shape course engagement, and the Gunuc and Kuzu approach treats peers as an extension of students' affective beliefs about the course. In each case, the agency of individuals in the classroom to create and participate in a network of peers is downplayed or ignored.

Third, all the scales neglect to assess cognitive engagement. The SCEQ attempts to measure a student's performance orientation, and asks questions about externalized behaviors that are proxies for cognition (as do the NSEE and Gunuc and Kuzu models). A model that includes cognitive engagement should focus instead on beliefs related to the course, like motivation to perform, that are related to cognition. Cognition, in and of itself, is difficult to capture, but a few instruments exist that can effectively assess motivation (Robbins, 2015), which is much more closely related to and predictive of cognition than behavioral engagement (Eccles, 2005).

This absence of theoretical and methodological attention to cognitive engagement in these popular models of course engagement results in several limitations. One of the significant limitations that stems from a lack of theorizing about engagement is that current models muddy the water between embodied practices (what students do) and internal influences (what students believe). Embodied practices and internal influences are mutually constitutive; such that external behaviors shape beliefs through interactions with actors and resources and beliefs shape what behaviors students will engage in throughout the course. An approach guided by a clear theoretical perspective that examines both the process of engagement and the outcomes of engagement would provide researchers and instructors important insight into both (Janosz, 2012). Such an approach could also be extended to other educational research pursuits where engagement and resource use are major driving factors of inquiry like learning analytics research and computer mediated instruction (CMI) in undergraduate education. In both learning analytics (Shum & Ferguson, 2012) and CMI research (Henrie et al., 2015), scholarship too often elides the cognitive, affective, and social aspects of

learning as well as the importance of instruction in shaping student course engagement (Gašević, Dawson, Rogers, & Gašević, 2016a).

Another limitation of the current conceptualizations of undergraduate course engagement is the way that all three approaches ignore time as a factor that influences engagement. For the purposes of the NSSE, this limitation is baked in to the design. The goal is to produce a campus snapshot (McCormick, Kinzie, Gonyea, 2013) of engagement, not to trace students' engagement through their academic careers, which can vary widely. Both the SCEQ and the model developed by Gunuc and Kuzu simply bypass the question of time. The instruments are designed to collect cross-sectional data. This is not unusual in that assessment of student engagement tends to treat engagement as an outcome rather than a time-sensitive process that yields an outcome (Mandernach, 2015). The current approaches thus fail to conceptualize students' engagement with course resources as a dynamic ongoing process where cognition, affect, and behavior influence each other and produce academic outcomes.

Perhaps the most significant limitation of the current models is that they fail to account for the complex influence of instruction on what students believe about a course and what they do as part of their academic performance. The SCEQ focuses on internalized influences without accounting for embodied practices. The Gunuc and Kunzu model focuses on externalized practices and relationships, without drawing clear distinctions around mental and behavioral influences.

Each university course is composed of a mix of actors (instructors, students, teaching assistants) and artifacts (syllabi, learning management systems, textbooks), which evolve over the course of each class period and the duration of the semester. To understand educational practice, researchers should analyze “the interactive web of actors, artifacts, and the situation” and their distribution throughout the space and time of a course (Spillane, Halverson, & Diamond, 2001, p. 23).

Approaching courses from the perspective of a system of activity can reveal the interactions between actors as well as between actors and artifacts, through which individual learning is mobilized. An activity system perspective affords analysis of behavior and coordination at a variety of levels differentiating between system activity, agentic action (of individuals), and concrete behaviors and operations (Ludvigsen, Havnes, and Lahn (2003, p. 296). Cohen and Ball (1999) proposed the instructional triangle as a framework for discussing the web of relations in the classroom, providing a context within which we can explore activities, actions, and behaviors. The triangle is composed of actors like students and instructors and tools like textbooks, learning management systems, and assessments. The arrangement of these resources produces an instructional system where teaching and learning is fostered through interactions between actors (student/instructor and student/student) and between actors and tools (student/technology and instructor/technology).

The instructional activity system is an extension of Engeström's (2000) activity system, which separates work into three domains: distribution, exchange, and production. Distribution is the work accomplished by the community within the division of labor to coordinate production of the outcome/object. Production is how the subjects of the activity system use the tools to produce the outcome/object. Exchange involves the rules of the activity system as negotiated by the subject and the community in the production of the outcome/object.

In the instructional activity system, the instructor (subject) enrolls students into the learning process using instructional tools. The instructional activity system should be "understood as tool-mediated activities in a collective enterprise interacting with other enterprises" (Ludvigsen, Havnes, & Lahn, 2003, p. 296). This process involves a series of exchanges—disciplinary, classroom, technological—that set the rules of instruction. The division of labor between the community (which includes students in the classroom and disciplinary agents like textbook authors and theorists

who are often at a distance in time and space), and the instructor dictates who does what work to accomplish production/learning. As such, each agent has some responsibility for producing learning.

Especially in higher education, researchers are interested in the conscious actions of instructors and institutional agents to foster learning and engagement on campus (Zepke, 2013). The vast majority of research on course-work engagement focuses on instructional strategies (Tinto, 2010; Wimpenny & Savin-Baden, 2013) with less attention paid to the relationships between students and the emergence of a learning community in the course. Few studies consider the role of the discipline or the curriculum in shaping engagement (Zepke, 2013).

Engagement with Course-work and Learning Resources. Considering the limitations to the current models outlined above, I argue for a multi-dimensional perspective on course engagement that conceptualizes influences on engagement and resource use in behavioral, cognitive, and emotional terms. Behavioral engagement includes attendance at lectures sessions, completion of assignments and homework, and participation in-class discussions (Kahu, 2013). Cognitive engagement refers to students' expectancies for success and their subjective beliefs about the value of course tasks, as well as the mental effort involved in a task or series of tasks (Eccles, 2015). Emotional engagement includes a student's positive and negative feelings about peers in the course and at the institution (Rovai, 2002). In the next three sections, I briefly review the literature on cognitive, affective, and behavioral course engagement. I provide an overview of how each is conceptualized in this study, the relevant literature that supports the current approach, and any limitations that stem from that literature. I pay attention to students' behavioral engagement with peers in a course and with digital instructional tools.

Cognitive Engagement. Conceptualizations of cognitive engagement usually take the investment of psychological energy as their starting point (e.g. Newmann, et al., 1992; Wehlag et al., 1989). Students are cognitively engaged when they develop strategies for approaching learning tasks,

such as in self-regulation (Pintrich & DeGroot, 1990). Researchers are generally interested in describing and analyzing how students display mental effort, and what factors shape and influence their investment in different learning strategies (Eccles, 2005; Pintrich 2004).

The scholarship on cognitive engagement draws concepts from the research on learning strategies and motivation (Fredricks, Blumenfeld, & Paris, 2004). Treating cognitive engagement as part of the process of course engagement, researchers aim to document psychological effort like volition (Fredricks et al., 2004) which encompasses “psychological control processes” (Corno, 1993, p. 16) that direct students’ efforts. Volition is a key concept, as it denotes cognitive or psychological effort; mental effort as opposed to behavior (Fredricks, et al., 2004). Self-directed psychological effort is important for course-work engagement, as students are presumed to have agency to make decisions about their study strategies, perhaps more so in post-secondary education than in other formal instructional contexts.

As students become engaged in a course, they develop different levels of investment in the material and have different motivations to learn (Pintrich 2000). Students may have little investment in the material, but are motivated to perform well in the course to obtain other opportunities that flow from high levels of performance (Perez, Cromley, & Kaplan, 2014). Alternatively, they may be unconcerned with performance metrics, but are passionately invested in the material. Interest and performance might be salient for students at different times in the same course. In both cases, we might expect students to perform well in the course, but their motivations to invest in course resources differ. As such, their selection of course resources might also differ. To understand students’ cognitive engagement, we should turn our attention to their motivations and course-work investment.

Course Beliefs. Students' motivations to invest in performance-oriented behaviors are informed by their expectations and beliefs about their own ability to be successful. Eccles' Expectancy-Value Theory (EVT) provides a model for examining the choices that students make in the context of performance and achievement-related tasks (Wigfield, Tonks, & Eccles, 2004). Students' approach academic tasks with a set of beliefs about the value of a task as well as expectations for their ability to be successful at said task (Eccles, 1994; Eccles, 2009; Wigfield & Eccles, 2000). Perez (2012) argued, for example, that students were,

most likely to choose a major in which they expect to be successful, where they believe they can meet the demands of the major. However, expecting to be successful is not enough. Student must find value in choosing the major (p. 13).

Eccles' theory identifies two important components of motivation. Expectations inform performance-oriented behaviors, as do perceptions about the tasks and costs involved in achieving high levels of performance.

First, individuals have expectations for success as it relates to their performance on a future task (Wigfield & Eccles, 2002). Expectancies for success are informed by external factors like the availability of resources (or the perception of that availability), which makes expectancies for success distinct from self-efficacy (Schunk & Pajares, 2009). Expectancies for success could reflect either 1) beliefs about one's academic ability or 2) beliefs about the challenge (or lack thereof) in a course, or both (Perez, 2012). In the classroom, expectations can "affect students' motivation, engagement, and investment of effort in learning" (Konings, Brand-Gruwel, van Merriënboer, and Boers, 2008, p. 536).

Individuals also possess subjective beliefs about the value of a task (Eccles, 2009). Subjective task value contains four components: attainment value, or the importance of a task to an individual's identity (Eccles, 2009; Torres, 2012); intrinsic value, or the anticipated enjoyment of a task (Eccles, 2009; Wigfield, Tonks, & Klauda, 2009); utility value, or the relevance of a task to future goals and

plans; and perceived cost, or the lost opportunities, lost effort, and emotional cost of completing an activity successfully (Flake, Barron, Hulleman, McCoach, & Welsh, 2015; Wigfield & Eccles, 2000).

Students consider their expectations for success and task value beliefs while making academic choices. Differences in expectations and beliefs can result in vastly different task performance among individuals with seemingly identical abilities. For example, Meece, Wigfield, and Eccles (1990) observed that expectancy beliefs were significantly related to math grades in high school, while task values predicted students' intentions to take further high school math courses; a finding that was reinforced in subsequent research by Updegraff, Eccles, Barber, & O'Brien (1996). In fact, task-values consistently predict student achievement (e.g. Cole, Bergin, & Whitaker, Steinmayr & Spinath, 2007; Viljaranta, Lerkkanen, Poikkeus, Aunola & Nurmi, 2009; VanZile-Tamsen, 2001).

Expectancy-Value Beliefs and Course Outcomes. Expectations, task value, and perceived cost play a major role in the academic choices that students make. For example, highly rating the subjective task value of science course-work was significantly related to students' likelihood to persist in STEM majors (Perez, Cromley, & Kaplan, 2014). Undergraduate women who were career oriented as opposed to family oriented and placed high task value on graduate education was significantly more likely to pursue advanced degrees (Battle & Wigfield, 2003). High perceived cost, especially the loss of valued alternatives, can deter student persistence in STEM programs (Perez et al., 2014). High perceived costs can broadly deter students out of investing time in mathematics course-work as well (Flake et al., 2015). Alignment of students' goals with the instructional approach can encourage (or deter if not aligned) students' engagement (Battle & Wigfield, 2003).

Expectancy Value Theory and engagement have substantial overlap. A student is not engaged unless she is committed and invested in a course, and Eccles' theory speaks specifically to

how commitment and investment form. An expectancy-value approach also allows researchers to document varying levels of engagement based on expectations and task values. For example, Gasiewski, Eagan, Garcia, Hurtado, & Chang (2012) observed that students who aspired to attend medical school have higher levels of academic engagement than their peers. As the authors note, “these students likely recognized the need to do well in science courses and assessed the value of the task higher than students that were undeclared” (p. 243). For the purposes of this study, I refer to the Expectancy Values constructs as course beliefs.

Affective Engagement. Students’ affective engagements are composed of their reactions to the classroom and campus environment, including feelings of belonging (Finn, 1989), as well as “interest, boredom, happiness, sadness, and anxiety” (Fredricks et al., 2004, p. 63). College students’ affective beliefs, their perception of connection to a campus community, can have a profound influence on their ability to persist and achieve (Pascarella & Terenzini, 2005; Strayhorn, 2012). Classroom and school environments with a strong sense of community, that is, where students feel accepted, and encouraged by their peers, foster engagement (Juvonen, Espinoza, & Knifsend, 2012). On college campuses, the closer to the center of campus life a student feels, the more likely she is to persist (Tinto, 1987). To be estranged from communal beliefs, values, or norms can result in social isolation and can impact students’ cognitive and affective functioning (Hofman, Hofman, & Guldemond, 2001). When students receive academic, social, and emotional support on campus they exhibit higher levels of engagement and have a greater likelihood of persistence (Tinto, 1987).

A sense of connection to campus life, where students perceive that social support is available and that they are important to others on campus, promotes the investment of energy in academics, peer relationships, and co-curricular activities that lead to academic success (Astin, 1993). Most research on students’ in higher education focuses on the macro environment of the campus (e.g. Gasiewski et al., 2012; Strayhorn, 2012). Yet, students possess multiple community memberships.

First, students are members of multiple learning communities organized around classes and extra-curricular programs (Cheng, 2004). Second, students belong to the larger campus community (Freeman & Anderman, 2007). The learning community membership is contextual and may only exist in certain spaces at certain times, given the salience of a course in a students' academic and social life. The campus membership would appear more durable, however, evolving across a students' undergraduate experience (and may subsume within it many of the students' learning community experiences).

Classroom and Campus Sense of Community. In the interest of addressing these two communities on campus, Rovai, Wighting, & Lucking (2004) developed a measure named the Classroom and School Community Inventory (CSCI), which uses separate scales to assess students' sense of community in the school and within a specific classroom. The CSCI can discriminate between learning and social communities and between social and academic connections. A sense of belonging, where students perceive social support from their peers and instructors and where they feel like active members of the institution, can promote academic achievement, retention, and persistence (Hausmann, Schofield, & Woods, 2007; Rhee, 2008). Students are unlikely to remain academically engaged and perform in their course-work if they do not feel personally valued and welcomed (Goodenow, 1993; Strayhorn, 2012). Sense of belonging is also situation and context-dependent, such that students function best in the context where they feel connection to a community that satisfies their needs (Osterman, 2000). Connection to a community, based on the perception that an individual is valued by others, is particularly important for students who are likely to find themselves underrepresented or marginalized in different social contexts (Hurtado & Carter, 1997) like Students of Color and women in STEM courses (Strayhorn, 2012).

Although few researchers have examined course-work engagement as a function of sense of belonging to classroom and campus communities, some substantial evidence suggests that sense of

belonging and community influence cognitive aspects of engagement like motivation. For example, in a survey of freshman at one institution, Freeman, Anderman, & Jensen (2007) observed significant relationships between students' sense of class belonging, defined as being valued by others in the course and perceiving social support available from peers, and students' intrinsic motivation and subjective task values. The researchers also identified a relationship between instructors' warmth, openness, and encouragement in-class participation with class level sense of belonging. Communication between and among students either face-to-face or through mediating technology increased students' perception that they were connected to and valued by others in the classroom on the CSCI (Dawson, 2006) as did in-class interactions (Dawson, 2008) and interactive instructional activities (Summers & Svinicki, 2007). In this way, sense of classroom community informs and is informed by students' behavioral engagement in the classroom.

Although affective engagement encompasses a broad range of feelings and emotions, for the purposes of this study I focus on affective beliefs that center on the social and academic community of a course. I focus on this set of beliefs because I believe the role of the course community (and feelings about that community) have been neglected in research on student engagement in post-secondary education. I leave boredom, sadness, and happiness to other scholars.

Behavioral Engagement. Conceptualizations of behavioral engagement differ the most between the broader empirical literature on K-12 education and the more task-focused approach of the literature on undergraduate education. Much of this stems from K-12 researchers' perspective on student behavior, where concerns about truancy, rule following, and disruptive behavior are salient (e.g. Appleton, Christenson, & Furlong, 2008). The more common approach in higher education research (which overlaps with some of the interests of K-12 researchers) is student participation in-classroom activities and in extra-curricular programs (Harper & Quaye, 2014).

Substantial evidence suggests that the indicators of behavioral engagement (time on task, participation, attendance, involvement in campus activities) are significantly related to academic performance and persistence in undergraduate education (Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008; Trowler, 2010). The relationship between campus involvement and student success is arguably orthodoxy in post-secondary research and practice (e.g., Pascarella & Terenzini, 2005). A consequence of the widely accepted belief is a neglect of a theoretically driven understanding of how behavioral engagements might differ depending on the source of the interaction. Peer-to-peer (or actor-to-actor) interaction is substantially different from student-to-technology interaction (or actor-to-tool), but little research on behavioral engagement attempts to consider these two behaviors in tandem.

Interactions with Peers. Peer interactions matter in college as they do in most educational environments (Coates & McCormick, 2014). Peers play a role in what students do outside of the classroom on campus, where students who engage with peers frequently report greater satisfaction with their undergraduate experience (Krause, McInnis, & Welle, 2003). A small number of social connections, perhaps as few as two or three (Chamblis, 2014), can positively impact a student's participation in campus life activities like clubs and organizations, which is related to higher levels of performance in courses.

However, very little is known about the mechanisms that facilitate academic performance as a byproduct of student interactions (both formal and informal) in a large lecture hall context. Researchers can assert that social ties matter, but they have yet to illustrate how interaction influences performance (e.g. Brewe, Kramer, & Sawtelle, 2012; Rizzuto, LeDoux, & Hatala, 2009; Yang, Nainabasti, Brookes, & Brewe, 2014). As Dawson (2010) argued,

Although it is now accepted that a student's social network is central for facilitating the learning process, there has been limited investigation of how networks are developed, composed, maintained, and abandoned.

Instead, the focus on social learning tends to examine student interaction in isolation from the larger network that shapes and structures interaction (e.g. Rizzuto, 2009).

Researchers increasingly assert that learning is a social activity in large lecture hall science courses where meaning is co-constructed through interaction (Dori & Belcher, 2005). Evidence of the importance of interaction to learning is especially apparent in math and science where work is often completed in pairs or small groups (Callahan 2008; Deslauriers, Schelew, & Wieman, 2011). For example, students who engage with peers in physics outperform students who work independently (e.g. Brewster, Kramer, & Sawtelle, 2012; Bruun & Brewster, 2013; Crouch & Mazur, 2001; Mazur, 2009). Intentional engagement with peers, what some scholars refer to as agentic engagement (Reeve, 2013), seems to lead to the greatest benefit for students. As such, it would be useful for scholars and practitioners to understand the factors that structure students' agency to select out-of-class study group partners.

This contrasts with the literature that examines naturally occurring peer effects, where students are randomly assigned to some role (e.g. classmates or roommates). The results of random assignment are, at best, mixed. For example, some researchers found small but significant effect of roommate assignment on academic performance especially for students in the hard sciences (Scaredote, 2001; Zimmerman, 2003), whereas others observed no significant relationship for academic performance between roommates or friends (Foster 2006) or between classmates (Hoel, Parker, & Rivenburg, 2005).

Research that focuses on course-based interactions as part of a classroom learning network among peers present a clear trend of influence. The social network is not precisely equivalent to the kind of social ties that influence student performance. Still, attempting to disentangle academic networks from social networks may be missing the point of peer social connections on campus. For undergraduate students, academic and social worlds are enmeshed (Nespor, 1994), an effect even

more pronounced for students in STEM fields (Brewer et al., 2012; Forsman, Linder, Moll, Fraser, & Andersson, 2012; Forsman, Moll, & Linder, 2014). The informal learning community fostered inside of a course can expand beyond the course boundary, providing students with access to peers with informational and social support resources that promote academic success (Yang et al., 2014). Peer interactions can thus motivate students to focus on academic performance (Summers, 2006).

Undergraduate students in-classrooms that are organized to support interaction post greater learning gains than their peers in traditional lectures (Baepler, Walker, & Driessen, 2014; Ge & Land, 2003). Peer networks in a course can provide important informational support, which is crucial for academic success (Canche, D'Amico, Rios-Aguilar, & Salas, 2014; Carrolan, 2013). Peer interaction supports individual reflection on course content and on students' learning strategies through social discourse (Lin et al., 1999), and has been linked to “cognitive development, identity development, self-confidence, self-efficacy, and social and academic integration into the university” (Callahan, 2008, p. 361).

Students may derive the most benefit from interactions that are centered on academic work and the concepts of a course. Students who had high levels of academic-centered peer interactions performed better than expected in undergraduate math lectures (Callahan 2008). Interacting with peers in informal learning situations, as occurs during out- of-class study time, improved student academic performance in physics courses (Brewer et al., 2012; Bruun & Brewer, 2013; Yang et al., 2014). What is unclear in these studies is whether simply spending time studying is the mechanism that improves performance, or spending time *collaborating with other students* improves performance. Examining other learning behaviors (like digital instructional technologies that students use to review course material) could help isolate the source of influence on student performance.

Researchers who focus on peer interactions in-classrooms identify the value in asking questions, providing explanations, elaboration, and receiving feedback (Webb, 1989). Students

become actively engaged in learning by resolving dissonance between their existing knowledge and new information through peer interaction (Kozulin, 1998). For example, students who engage in group processing of in-classroom activities do better on higher order assessments than students who work independently (Linton, Farmer, & Peterson, 2014). Collaboration during learning activities promotes: “collective induction, generative learning, and metacognitive learning” (McNeese, 2000, p. 166). The benefits of peer interaction to learning appear contingent upon high levels of interaction and the dynamics of student groups (which facilitate engagement and feedback) (Webb, 1991).

The nature of peer interactions also results in contextual and dynamic influence on student learning. Positive interactions (like providing social and informational support) might spur student success while negative interactions (like distracting a peer) might deter it (Carrolan, 2012). Students enter a classroom with competing demands on their time and are generally required to make choices about what to read, watch, and do. Consequently, not all course interaction between students is beneficial. During class time, peers can distract other students or help keep them on task, especially in-classrooms where the space is conducive to interaction (Baepler et al., 2014).

Competition between peers in the classroom may prevent students from sharing knowledge or ideas with others. In their qualitative study of student interactions in-classrooms, Seymour & Hewitt (1997) observed that competitive classroom environments like those found in undergraduate math courses can warp peer interactions, resulting in suspicion between peers and isolation.

Instruction and Peer Resource Use. One of the primary ways that instructors can facilitate the kind of peer interaction that might facilitate out-of-class study partnerships is by using interactive engagement strategies. The traditional lecture format, where an instructor provides information as the sage on the stage (Losh, 2014; Selwyn, 2014), appears to be losing ground in American higher education (Rocca 2010). Over the last two decades faculty members have begun to incorporate instructional approaches that are increasingly student-centered (Eagan, Stolzenberg, Berdan Lozano,

Aragon, Ramirez Suchard, & Hurtado, 2014), resulting in a reorganization of post-secondary classroom instruction, especially in large introductory lecture courses (Selwyn, 2014). An increasing body of evidence suggests that student-focused instructional strategies like peer learning (Topping 2005), peer assessment (Boud, Cohen, & Sampson, 1999; Topping 1998), and collaborative learning (Johnson, Johnson, & Smith, 2007) appear to improve student performance and retention especially in post-secondary natural sciences (Mallette and Cabrera, 1991; although some researchers take issue with this conclusion.¹ Cooperative classroom environments have been linked to gains in student achievement as well as increased motivation and persistence in undergraduate education (Pascarella & Terenzini, 2005). This attention to interactive forms of instruction produces educational activities that are increasingly social (Linton et al., 2014).

The level of interactivity encouraged by instructional strategies may also influence social tie formation in the classroom. Faculty behaviors contribute to the classroom context, which can foster interaction and engagement (e.g. Chickering & Gamson, 1987; Ewell & Jones, 1996; Tinto, 2003). Using an information delivery approach may deter the development of social ties between students in the course, whereas a student-centered approach may foster social ties by encouraging students to interact with each other, although this might inevitably vary based on the instructional approach. While student-instructor interactions are an important influence on student course engagement in post-secondary education (Chamblis, 2014; Kuh, 2009; Astin, 1993; Pascarella & Terenzini), the large lecture hall makes direct student-to-instructor interaction more challenging (O'Brien, 2002).

To address this lack of interactivity between students and lecturers in large lecture hall courses, instructors have turned to interactive instructional strategies where students are encouraged to engage their peers during class time. Interactive instructional strategies have proved particularly

¹ Hora (2015) for example, argues that a systematic study of instructional practices is needed before scholars can argue for the superiority of any approach.

popular in undergraduate physics, where the study of physical phenomena is conducive to interaction and the need to correct misconceptions about the physical world is a core-learning objective in introductory courses (Docktor & Mestre, 2014).

In physics education, interactive engagement (IE) strategies lead to several desirable changes in the classroom. For example, in one study of two sections of a large introductory physics lecture, in the section that employed interactive engagement methods researchers observed increased student attendance, higher behavioral engagement, and greater learning gains (Deslauriers, Schelew, & Wieman, 2011). Researchers who compared interactive engagement (IE) strategies to traditional lectures across 62 sections of introductory physics found that students in courses scored substantially better on the Force Concepts Inventory² (two standard deviations higher on a standardized measure; Hake, 1998) when interactive approaches were used. Active learning strategies in physics courses at North Carolina State University (Beichner et al., 2007) and the Massachusetts Institute of Technology (Dori & Belcher, 2005) resulted in improved conceptual understanding and improved attitudes regarding the course experience.

In undergraduate physics education, some alternatives to traditional lecture have been developed to promote interactive participation. According to one survey of a representative sample of American Physics faculty, about 87% were aware of research-based instructional methods, with interactive participation strategies registering the highest awareness and use (Henderson & Dancy, 2009).

Instructional Moves. Instructors can also foster interaction with peer resources through their planned and unplanned instructional moves. During interactions with students, through their verbal cues and their body language, instructors can cultivate different environments in the classroom

² The Force Concept Inventory uses a pre and post-test exam to identify improvements in students' understanding of basic mechanics concepts in physics (Hestene, Wells, & Swackhamer, 1992).

(Rocca, 2010). An undergraduate course where mutual respect is promoted— where instructors express concern for students and encourage students to express concern for each other—is more conducive to participation (Crombie et al., 2003; Dallimore et al., 2004; Wade, 1994). Nonverbal immediacy behaviors, like eye contact, also promote participation and engagement (Rocca, 2009). In fact, the teacher’s actions in the classroom, what we might term their instructional moves, “are indeed most crucial in promoting classroom interaction” (Karps, & Yoel, 1976, p. 426). Instructors can cue students towards different resources by incorporating references into their talk, and by using instructional resource to illustrate a study strategy in the classroom.

The instructor’s moves can also deter engagement. In contrast to eye contact, instructors who ignore students, tease, or are overly critical are unlikely to promote participation and engagement (Kearney, Plax, Hays, & Ivery, 1991; Wade, 1994) resulting in the kind of classroom community that does not foster interaction. According to one study, the use of PowerPoint slides, while ubiquitous, prompts widespread boredom (Mann & Robinson, 2009). There are several factors that prevent students from participating through in-class interaction with the instructor including logistics, student confidence, and classroom climate (see Rocca, 2010 for a detailed overview of the literature on student participation in PSE classrooms).

A faculty member’s discipline can influence their instructional strategies, thereby influencing the level of interaction and engagement in a course. Disciplinary cultures and practices may, in fact, be the single most potent influence on faculty behavior (Smart, Feldman, & Ethington, 2000). Differences between disciplines as they relate to consensus of knowledge and methods for knowledge production and dissemination result in vastly different approaches to instruction (Nelson Laird et al., 2008), with low consensus fields like the humanities potentially placing more of an emphasis on improving instructional practice than high consensus fields like math and science (Braxton & Hargens, 1996). In recent years, given the emphasis and investment placed on producing

math and science degree holders (Ferrare & Hora, 2014), there may be an emerging consensus and interest in improving an individual's teaching. This certainly seems to be the case in physics, at least (Doktor & Mestre, 2014). Disciplinary regimes around teaching and learning may result in approaches that are more interactive (like the Socratic seminar in many humanities courses) or less interactive (like the sage on the stage lectures that historically were common in large lecture halls; Losh, 2014).

Most research on instructional strategies examines the variation among one or two practices to identify improvement, but few studies attempt to capture some of the range of strategies instructors employ (Hora, 2015). For example, in a series of studies of science, technology, engineering, and math professors who taught large lecture courses, Hora and his colleagues (e.g. Hora, 2015; Hora & Ferrare, 2014; Hora & Holden, 2013; Oleson & Hora, 2013) observed that instruction was composed of a variety of moves and strategies, including verbal, non-verbal, and artifact-based approaches. Instructors used visual slides, practice problems, demonstrations, and simulations to communicate concepts to students in addition to providing verbal explanations. Research should hold constant (or at least account for) many of the other instructional activities in the classroom. Existing research on the efficacy of different instructional practices, strategies and moves is limited, therefore, when they fail to provide a rich characterization of instructional work.

Additionally, much of the research on instructional strategy would be improved by considering how instructors and students, in concert, shape the instructional activity system. Interaction between instructors and students has a bi-directional effect, influencing instructors' moves and strategies as the course progresses (Pelletier, Seguin-Levesque, & Legault, 2002). When students' display little interest or engagement, or fail to participate, instructors may (intentionally or not) change how they relate to students (Pelletier et al., 2002). The instructional triangle, where students are positioned between instructors and tools in a mutually reinforcing relationship,

supports this notion. Students' in-classroom behaviors (and their performance on out-of-classroom assessments) can alter instructional moves and strategies either in the moment or in subsequent iterations of a course.

Social Network Theory and Classroom Learning Networks. While much of the existing evidence suggests that interaction benefits performance and that instructors can encourage performance through their instructional strategies, further research is needed that identifies the mechanisms that foster network formation in-classrooms as these networks structure the potential for interaction. A substantial theoretical literature identifies social mechanisms that foster (or deter) the development of social networks across social contexts. Yet, very little research has investigated these mechanisms in post-secondary classrooms. To understand how students engage their peers as part of their course-work engagement, insight is needed into how different network structures might influence social learning resource use. In networks, social mechanisms like the tendency to gravitate towards popular individuals (what's termed centrality), one's instinct to seek out others with similar background (homophily), or our impulse to connect with friends of friends (transitivity) could shape the opportunity to participate in out-of-class study groups. For some students, accessing formal or informal out-of-class study groups may simply be too high a cost given their position in the classroom learning network. For example, students who are unpopular in the network, or who are not central to the network's structure, may be unlikely to access out-of-class study groups. Individuals with a higher percentage of connections out of all potential connections are said to be central or have high centrality (Carolan, 2014). In some research, especially research on adolescents, centrality is treated as equivalent to popularity (Dishion, 2013). Researchers have demonstrated a link between popularity in a network and social behavior, like behavioral engagement in K-12 schooling and delinquency (Dishion, 2013).

There is some evidence that centrality is related to academic outcomes. The social connections a student possesses in large lecture courses appear to be positively related to their performance in the course (Bruun & Brewe, 2013; Dawson 2010; Rizzuto et al., 2009; Yang et al., 2014), such that students who were more ‘popular’ in the emergent network of a course academically out-performed students with fewer connections. Students in an online course who had higher levels of centrality (that is, students who had the highest levels of popularity as determined by the number of other students they connected to) performed at higher levels in the course (Dawson, 2010; Joksimović et al., 2016.; Joksimović, Gašević, Kovanović, Riecke, & Hatala, 2015), a finding echoed in offline lecture courses (Rizzuto et al., 2009). Being central to a network increases the potential for a student to receive social or instrumental support from their peers. It also provides students with a greater array of social resources to choose from. It might also be that students who are academically adept become more central because other students are more likely to seek them out. The relationship between centrality and academic performance is a question that needs more investigation.

Students’ popularity in a course network might be related to the identities and experiences they bring to campus. In most social contexts, tie formation between individuals is guided by homophily (Goodreau, Kitts, & Morris, 2009). Homophily refers to the tendency of individuals to seek out social ties with individuals who have similar identities or shared experiences (Biancani & McFarland, 2013). Undergraduate students on residential campuses tend to be close in age and have relatively homogenous backgrounds. If homophily is guiding the formation of the course networks within which peer interactions occur, students who are overrepresented on campus would seem to have an easier time developing social ties. For example, researchers observed that students of color on campus had fewer connections on campus than their white peers (e.g. DeFour & Hirsch, 1990; D’Augelli & Hershberger, 1993; Kenny & Stryker, 1996).

Homophilous peer interactions may result in learning environments where the benefits of interaction are unevenly distributed. In research at ten Texas universities using Facebook data, Mayer and Puller (2008) observed significant sorting among friendship groups by race/ethnicity, academic major program, and political beliefs. With fewer existing connections, students who are underrepresented in their major programs would appear to have fewer opportunities to benefit from the resources that flow from social connectedness. Women and racial/ethnic minorities, who are underrepresented in math and science major programs, are frequently excluded from interactive in-class learning activities (Callahan, 2008) as well as out-of-class study groups (e.g. Fox & Soller, 2001; Kennedy & Parks, 2000; Lin & Kessel, 1996; Rosser, 1997).

Given that students of color and women are substantially underrepresented in STEM disciplines, the reliance on naturally occurring peer interaction as an instructional strategy may exclude these students through social selection (Brown, 2015). In a study of the teaching method called Peer Instruction in an introductory undergraduate honors physics course, Brown (2015) reported substantial gender segregation where women and men had significantly higher odds of forming same gender collaborative groups in-classroom activities – even though women made up less than 20 percent of the students. Consequently, women were left with fewer potential partners, and were more susceptible to isolation during peer instructional activities. Of greatest concern, women who reported academic collaborators also had higher odds of being in the high-achieving group, in comparison to their isolated peers who did not (Brown, 2015).

In contrast, enrollment in diverse classroom environments may have the reverse effect. For example, Gonazelz-Canche and Rios Aguilar (2015) observed that students of color who were enrolled in community college courses with a diverse group of students (and therefore had the potential to collaborate with a diverse group of peers on course-work) did better on average than students who were in-classes with predominantly white peers. The demographic enrollment of a

course may structure the potential for peer interaction, especially in instructional contexts where peers can self-select collaborators for in-class activities.

The closed classroom network suggested by the research on homophily may also be a byproduct of the tendency towards “friend of a friend” tie formation in social networks; what’s been termed transitivity by social network researchers (Goodreau et al., 2009). Students are not only more likely to seek out individuals with similar identities and experiences, they are also likely to form relationships with individuals who are already connected to their larger networks (Biancani & McFarland, 2013). This means that students who are more likely to interact because of physical proximity and regular class meetings are also more likely to form durable relationships if they have shared identities, experiences, and social contacts in common (Goodreau et al., 2009).

The influence of peer interaction on students’ outcomes appears specific to the instructional system and the classroom learning network. Discipline, classroom configuration, classroom diversity, the nature of the interaction, the structure of the classroom learning network, and the impetus of the interaction (whether a formal instructional strategy or an informal social interaction) all need to be considered. The primary limitation of the current literature is that the complex social conditions around peer interactions are rarely given much attention. When they are considered in network research, a connection is treated as a control to help explain variation in individual performance (e.g. Rizzuto et al., 2009) as opposed to interdependency between two (or more) individuals. There is some evidence to suggest that the quality of a partner’s knowledge about a subject might impact a student’s outcomes (Hoel, Parker, & Rivenburg, 2006; Parker, Grant, Crouter, & Rivenburg, 2010), but no research in higher education has sought to model the interdependencies that might explain variation in outcomes (McFarland, Biehl, & Rawlings, 2011). Research is needed that explores interaction, in a course network, by modeling for the impact of interdependencies between students on individuals’ outcomes.

Digital Instructional Tools. Classroom learning is composed of interactions between the instructor and students, interactions among students, and interactions between students and content including instructional technologies (Ball & Cohen, 1998). As part of their behavioral engagement in a course, in lieu of interactions with peers and the instructor, students may turn their attention to easily accessible online tools provided as part of the course materials. Of course, students are equally as likely to use these tools as a complement to peer interaction as a replacement for it. Digital instructional tools, similar to peers, are a potential learning resource that students can access at different points in a course and with varying degrees of frequency.

Digital instructional tools take a variety of forms and serve a variety of purposes from information delivery to helping students develop concept mastery. What these tools have in common is that they provide a mediated educational experience, where students can engage with the course material liberated from the constraints of time and space placed on physical interactions with peers and instructors. In this way, digital instructional tools can be an appealing alternative learning resource for students, whether or not peer resources are available.

The mixture of face-to-face methods and with online tools for instruction is referred to as blending (Bonk & Graham, 2006; Drysdale, Graham, Spring, & Halverson, 2013; Graham, 2013). Blending draws upon “two historically separate models of teaching and learning: traditional face-to-face learning systems and distributed learning system” like distance and correspondence education (Graham, 2013, p. 5).

Digital instructional tools facilitate blended instruction. Digital instructional tools bridge the work of instruction and the process of individual learning in large courses by making course material available on-demand and in some cases making the material smart and adaptive to learners’ needs. Digital instructional tools

- Draw upon the affordances of the collaborative, participatory and distributed practices made possible by the Internet (Greenhow, Robelia, & Hughes, 2009).
- Are capable of rapid change, can be used in a variety of ways, and are opaque to the user/student (Koehler & Mishra, 2009).
- Are selected for a pedagogical purpose for a formal learning context (Lankshear & Knobel, 2006), although they may be configured in a variety of ways by the student/user.

Digital technology becomes an instructional tool when it is appropriated and translated for use in a curriculum by instructor(s). The learning management system (LMS) is a prototypical example of a digital instructional technology, as it has read-write capabilities, is organized and ‘authored’ by the instructor, and is put to a variety of uses by the student/user. Other examples include digital textbooks (which are less flexible in their design) and online homework systems (which are often inextricably linked to their digital textbook) that serve a variety of purposes, including information delivery, assessment of student learning, and as formative feedback for the instructor about student engagement through their analytics. Blended instruction is not possible without digital instructional technologies

In large lecture hall courses, much of the instructional material is digitized and placed in learning management systems to provide students’ instructional resources at a manageable scale (Coates, James, & Baldwin, 2005). Tools are broadly construed to include any material object around which a community of actors engaged in production of learning (or in-classrooms—teaching and learning; Engeström, 1990). Chalk as used during lectures is an instructional tool because it serves a specific information delivery purpose in the classroom. Tools are activated through their usage in instructional practices. While many material objects are used as tools in the instructional activity system, the use of digital instructional technology in large lecture halls is the predominant norm in higher education (Henrie et al., 2015).

Instructors are increasingly incorporating online tools into face-to-face teaching. Blended instructional approaches are forecasted to become “the new traditional model” (Ross & Gage, 2006, p. 168; Norberg, Dziuban, & Moskal, 2011; Watson, 2008). As of 2010, 2/3 of students enrolled in

degree seeking programs in higher education had received instruction with online tools (Radford 2011). Results of a recent survey by the Higher Education Research Institute report that nearly half of the instructors surveyed were using online tools to supplement face-to-face instruction of undergraduates (Eagan, Stolzenberg, Berdan Lozano, Aragon, Ramirez Suchard, & Hurtado, 2014).

Research on use of digital instructional tools and academic performance. According to one meta-analysis comparing courses where traditional lecture delivery was contrasted with blended instructional modalities (where some courses are taught using online asynchronous elements) and purely online instruction, on average students perform best in courses where face-to-face instruction and online technologies are combined (Bernard et al., 2014). Many studies of undergraduate education have observed that personalized support delivered through web-enabled tools improves student performance (e.g. McKay, Miller, & Tritz, 2012; Knight, Shum, & Littleton, 2014).

Simply using online tools doesn't seem to be sufficient to obtain learning gains (Bernard et al., 2014). Bonham et al. (2003) observed no significant difference in performance in an experimental study of introductory physics students who used a Web-based homework system in comparison to a traditional paper-based homework. Zerr (2007) observed similar results with students in introductory Calculus. In contrast, students in courses that use web enhanced activities, such as out-of-class exercises, did post significant gains over students in the traditional course control group (McFarlin, 2008). Incorporating web tools into course-work isn't enough; the task the resource addresses (or mediates) must be relevant and interesting to students (Mann & Robinson, 2009).

Research on student digital instructional technology use in post-secondary courses tends to focus largely on behavioral indicators, like trace data (Lonn, Aguilar, & Teasley, 2013). Every click on a web page or web-based application leaves a trace of the user's behavior. Researchers can aggregate this trace data to construct a profile of an individual's technology use (Krumm,

Waddington, Teasley, & Lonn, 2014). For example, researchers determined that students who logged into the learning management system soon after the lecture to download lecture slides did better, on average, than students who waited longer periods (You, 2016). The primary limitation of studies that rely almost exclusively on trace data is that they divorce individual behavior from internal beliefs and motivations regarding the behavior. In a review of studies on student engagement in technology mediated learning environments, Henrie et al (2015) observed that few studies of this type provided a holistic measure of student engagement with course material. Many studies reported that students who used some form of digital instructional technology— like Twitter (Junco, 2011), online learning management systems (Sun & Rueda, 2012), or clickers (Blasco-Arcas, Buil, Hernandez-Ortega, & Sese, 2013)—had higher levels of behavioral engagement in the course, although in each of these cases the object of study was an indicator of behavioral engagement.

Learning analytics researchers have been particularly interested in capitalizing on the potential for trace data to shed light on student achievement. Several attempts have been made to develop predictive models of student success from trace data about student behavior and historical data about students' academic performance (Baker & Inventado, 2014). For example, Junco and Clem (2015) studied the use of a digital textbook system by students in a few large lecture courses. The authors used a proprietary engagement index developed by the digital textbook manufacturer to predict students' grades. They determined that higher scores on the engagement index were significantly related to students' final grades in the course. When the researchers examined the components of the index, only the number of days a student spent reading was significant in comparison to bookmarking and taking notes. These results suggest that a purely behavioral index measure of engagement has little explanatory power.

While data about students' digital instructional tool use might hold value in understanding the level of engagement with course-work (Arnold & Pistilli, 2012), it is generally not a good

predictor of academic success on its own (Giesbers, Rienties, Tempelaar, & Gijsselaers, 2013). Instead, much like tools must be enfolded into educational practices to become instructional technology (Fenwick, Edwards, & Sawchuk, 2011), usage data gains explanatory power when it is considered in light of students' motivations (Giesbers et al., 2013). For example, the use of web-enabled audience response systems (e.g., clickers) produces educational benefits by encouraging peer interaction and active learning in a lecture hall (Blasco-Arcas, Buil, Hernández-Ortega, & Sese, 2013). The authors argue that the benefit is not derived, as it were, from clicking a device, but from the participation during class time that the clicker device facilitates/mediates. To understand this benefit, researchers should investigate the instructional practices that shape digital technology into instructional tools.

Instruction and Digital Instructional Technology Use. It is an oversimplification to treat trace data as a simple behavioral indicator without a full understanding of how a DIT is used in the course (Gašević et al., 2016a). Researchers need to characterize a technology, understanding how instructors encourage its use through their instructional strategy, and develop some insight for how students have adopted the technology if they plan to incorporate trace data into their models for student success. As a behavioral engagement with course resources, DITs need an accounting of their role in the instructional system and of their use in the course network.

Instructional practices play a large part in defining what is a tool and how a tool might be used in the classroom (Nespor, 2011). The variation that Bernard et al. (2014) observed, and the inconsistent results reported by other researchers about the impact of instructional technology use reflects the diverse ways that the same technologies can be applied in different classrooms (Gašević et al., 2016). Instructors may widely adopt tools like LMSs or digital textbooks, but they use them in idiosyncratic ways that behavioral engagement models don't reflect. Contextualizing behavioral data

within information about students' peer engagements in the instructional context could improve the information that these models provide to students and to instructors.

Junco & Clem's (2015) results highlight a consistent limitation across much of the learning analytics literature on course resource use. The bulk of the analyses in these studies occur after the instructional work has ended and focuses on individual students in isolation from their peer interactions and the instructional context. In fact, the aim of this work is to, in part, develop predictive models of risk that are context neutral (e.g. Jayaprakash et al., 2014). Developing generalized models for student success like the textbook use measures referenced above results in models with limited explanatory power. Context, discipline, curriculum, and instruction all matter for student success, such that when learning analytics scholars do account for these differences they find no result that is significant across disciplinary contexts either in online courses (Finnegan, Morris, & Lee, 2008) or in face-to-face instruction (Brown, DeMonbrun, Lonn, Aguilar, & Teasley, 2016). In fact, differences in disciplinary practices may be one of the primary factors driving differences in performance across undergraduate general education (Brown, et al., 2016). Accommodating for contextual factors, instructional practice, and learning community idiosyncrasies might improve the predictive power of learning analytics applications. These models underestimate the potential influence of peers and the crucial influence of the instructional context.

Conceptual Framework

In educational research, social interactions and technology use are most often treated as conceptually distinct interactions even though engagement is produced through interactions both with peers and DITs. Students participate in a social system in the classroom composed of peers and the instructor, where they co-construct meaning through interaction and dialogue (Yang et al., 2014). As part of their learning, especially in large lecture halls, they also interact with digital instructional technologies (DITs) that liberate learning from the constraints of time and space (Graham, 2013).

These two kinds of interactions are conditioned and catalyzed by a student's motivation and their affective beliefs. To improve both research and practice, we need a conceptualization of course engagement that accommodates social and technological interactions as part of the process of engagement.

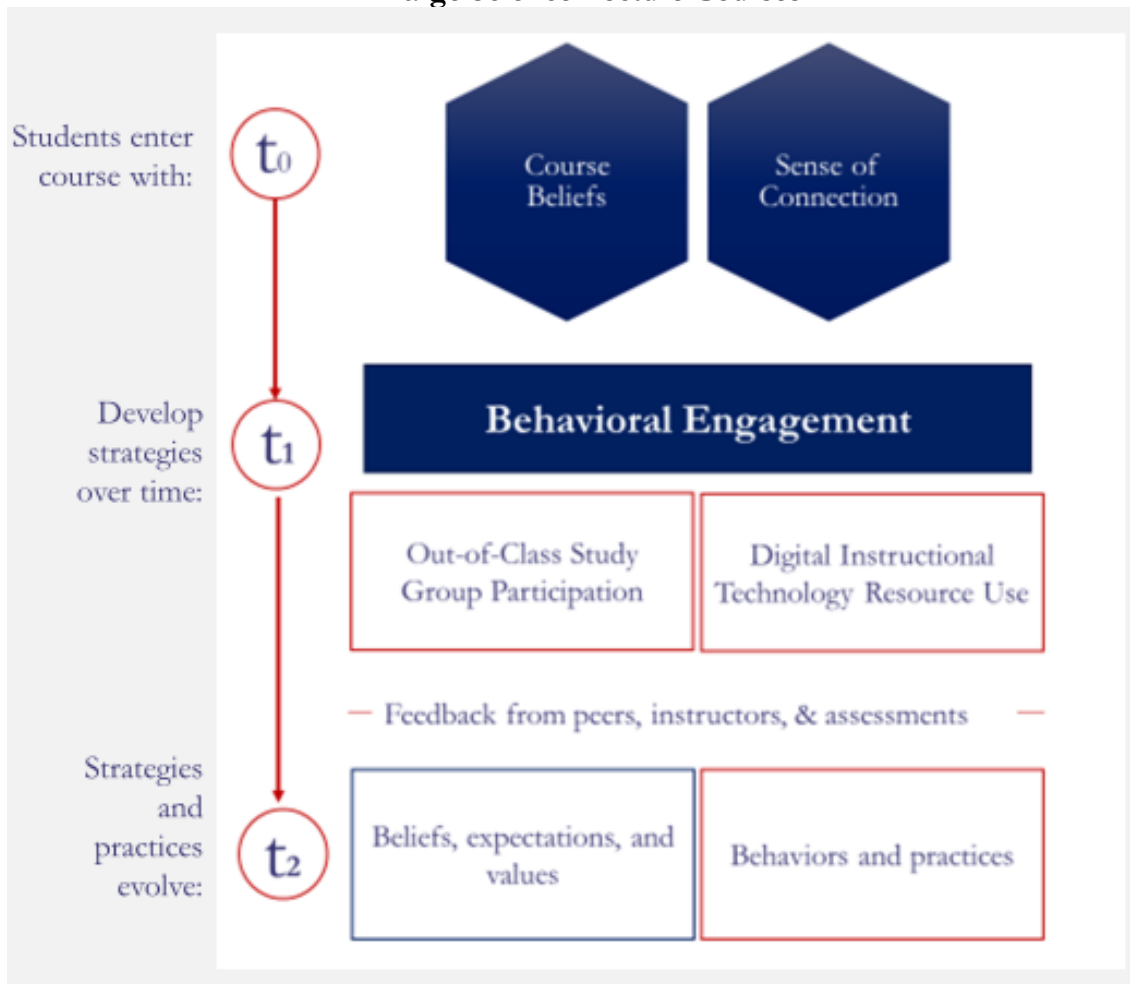
The current literature on promotion and retention in higher education would suggest that as students gravitate away from their peers—from a feeling of being connected to and valued by peers in a course—their academic performances will suffer (e.g. Freeman, Andersen, & Jensen, 2007). We simply do not know enough about peer networks in large lecture courses to make generalizable arguments about what resources merit institutional investment, or what strategies we should be encouraging students to adopt across disciplinary and instructional contexts in the sciences. A network perspective allows us to conceive of course-work engagement as something that co-evolves alongside students' social and technological interactions. Networks are ideally suited to conceptualize co-evolutionary behaviors because they can account for structure, agency, and interdependency (Snijders, Van de Bunt, & Steglich, 2010).

Research is needed that attempts to model social and technology enhanced behavioral engagement in large lecture hall science courses. Scholars often rely on cross-sectional measure of course engagement; on decontextualized measures of peer influence; on methodological individualism when modeling student success. The course network is secondary to the behaviors of the individual, as if the learning of an individual could be easily extricated from the instructional context. The research I propose would redress those shortcomings by treating student course engagement as an iterative process that co-evolves with the formation of a network in the course. Student success can be understood and modeled relative to the formative feedback of assessments, the connections students share with peers, and the behavioral strategies that students engage in and

develop throughout a course. I have depicted this conceptualization of how students become engaged in course-work in large science lecture courses through learning resource use in Figure 2.

The network perspective locates students in a bounded community of potential peers and a collection of available instructional technologies. Students enter a course with beliefs about the campus community, the (potential) classroom community, and the course (as shown at time 0; t_0). Beliefs about the course encompass expectations for success, subjective beliefs about the value of course tasks, and perceived costs related to the course (Perez et al., 2014). In this study, I conceptualize expectations, task values, and perceived costs as beliefs students bring into the classroom that shape their initial learning resource use (time 1; t_1). Through feedback from their use of learning resources, from classroom assessments, and from peers and instructors, students' expectations, values, and costs might change, which influences behavioral engagement (time 2; t_2). Through out-of-class study interactions their sense of being valued and connected to peers may also evolve (t_2). When choosing among learning resources, I expect that students will choose resources that align with their motivations to invest (or not) in a course and with their self-efficacy as it relates to use including their technological proficiency. Similarly, students' beliefs about the social and academic community in a course might influence their decision to adopt social resources, which catalyze and conditions their choices among social and technological resources.

Figure 2. How Students Become Engaged in Course-work in Large Science Lecture Courses



Through their preferences and behaviors students construct learning strategies that support their academic goals in the course (time 1; t_1). Feedback from instructors and from digital instructional tools can affect the choices that students make among the available array of potential resources, and the experience of using the technology may also affect its future use (t_2). This process of use, reflection on, and refinement of, use strategies is part of the social shaping of technology (Williams & Edge, 1996). At the same time, assessment feedback might also influence students' internal beliefs about the course including the difficulty of the subject matter, a student's potential for success, and their willingness to expend time and energy to achieve their initial goal (t_2). Over

time, their network position may change as they seek out more or fewer peer resources and invest time in DIT use. In the next chapter, I outline the methodological approach to validating this proposed framework.

Chapter 3: Research Design

In this study, I map the instructional system in a large undergraduate science course by employing social network methodology (to understand the interactions among students), learning analytics data (to understand the interaction between students and instructional tools available through the course management platform), and data from observations of instruction (to understand the interaction between instructors with students *and* tools). Bringing together these three complementary approaches allows me to address my primary research questions:

1. How does the instructional system shape students' engagement in peer interactions and their use of digital instructional technologies in a physics lecture course?
2. What are the relationships among students' peer interactions, their digital instructional technology use, and their performance on assessments in a physics lecture course?

In this chapter, I first provide an overview of the methods I will use to answer these questions. Next, I describe the design of the study, including the research setting, participants, data collection, and analysis plans. In the data collection section, I also describe in brief the pilot studies that helped clarify the design of the current study, with special attention to development of the survey instrument. A discussion of validity concerns and the limitations of the study follow. I close by enumerating the contributions and significance of the study for higher education research and practice.

Table 1. Research Questions, Goals, Methods, and Analyses

What do I need to know? (Research questions)	Why do I need to know this? (Goals)	What kind of data will answer the questions? (Methods)	Analysis methods
RQ1A: How does the instructional system shape students' engagement in peer interactions and their use of technological tools in a large lecture course?	Identify how the instructional system encourages or deters students from adopting different learning behaviors	Data from instructional observations; Visualization of course networks over time and socio-metric data about changes to peer resource interaction; Digital trace data from DITs.	Descriptive network visualization and analysis of observations of instruction
RQ2A: What is the relationship between students' peer interactions and their technological resource usage?	Understand the relationship among different configurations of course resource use	Digital trace data from digital instructional tools; Survey data from students including socio-metric data; Assessment data from exams	Stochastic Actor Based Modeling of network and behavior change
RQ2B: What are the relationships among students' peer interactions, their digital instructional technology use, and their performance on assessments in a physics lecture course?	Understand how different configurations of course resource use impacts student performance	Digital trace data from digital instructional tools; Survey data from students including socio-metric data; Assessment data from exams	Fixed Effects Linear Modeling

Methodology

Classrooms are specific social contexts with their own cultures, attendant roles for individuals, and resource availability. Each student in a classroom is simultaneously a potential social resource and a consumer of peer and technological resources. The dual role of each student – as resource and as consumer – requires a theoretical, methodological, and analytical approach that examines interdependent influences, resources, and outcomes. This is the primary affordance of network methods (Robins, 2015).

Educational research is susceptible to methodological individualism, where the focal actor, participant, or subject is often divorced from their context and their social relationships (Arrow, 1994). Social network research is one approach that provides a corrective to this limitation, by

locating individuals in a network of social connections, and offering potential explanations for behaviors and preferences as a function of their network position (Daly, 2010). By combining social network and learning analytic tools into social network learning analytics I can account for the dual role of students while richly characterizing their behavior through data about their digital instructional technology use. Although many foundational social network studies have focused on the social world of higher education institutions, few scholars have pursued the study of undergraduate students' social worlds in the classroom (Biancini & McFarland, 2013).

Social Network Analysis. Social network methodology is particularly well suited to explorations of resource selection. A long tradition of research, much of it higher education contexts, seeks to explain how individuals form and maintain social connections over time (e.g. Festinger, Schacter, & Back, 1950; Friedkin, 1978; Newcomb, 1962). In the wake of this work, researchers have also investigated how individuals access these connections to gain different resources and benefits, like informational, social, and instrumental support (Carrolan, 2008; Nespore, 1994; Small et. al, 2015).

Adopting a social network methodology encourages a focus on the structure of social relations and dependence in those social relations (Robins, 2015). In network studies, structure and dependence are investigated by focusing on actors (individuals), their social ties (connections and relationships between individuals), and the networks of individuals that form around them (Wasserman & Faust, 1994). Because classrooms are specific social contexts, each with their own culture, attendant roles for individuals, and resource availability (McFarland et al., 2011), network analysis is a useful tool for understanding the structures and dependencies that emerge because of instruction, peer interactions, and students' use of various instructional tools in a classroom.

Structure – in the tradition of social network research – refers to the network of relationships, called network ties, between actors that affords and constrains communication and

resource sharing (Wasserman & Faust, 1994). Dependence refers to the simultaneous influence of a tie on two or more actors.

In-classroom studies, dependence is largely overlooked, especially in quantitative research, because traditional linear regression models operate on an assumption of independence between covariates (McFarland et al., 2011). In contrast, social network studies explicitly investigate how structure in communities emerges from interdependence, and how the resulting infrastructure of relationships facilitates or deters resource sharing. Actors are presumed to engage in a “creative processes of selection between possible choices of action” that are influenced by social relationships and social structures (p. 47). In this way, social network methods better approximate the model of course engagement offered in this study, where behavior is a function of rational cognition and creative affective reflection on possible courses of action.

Data in social network methods. All network methods contain some elements of qualitative and quantitative methodology (Bellotti, 2014). First, the ties that bind a network together are characterized qualitatively (i.e., as friendship, kinship, professional connections, organizational ties). To understand how the identities and roles of actors shape the formation of social ties and the sharing of resources through ties, researchers need to also characterize the context—most often through interviews with participants or through direct observation (Bellotti, 2014). Second, network ties are quantified to produce measures of network features like the frequency of connections between individuals and the probability that individuals within the network return a social connection (Borgatti & Daly, 2014).

In this study, the context encompasses the relationships among students as well as the physical environment of the classroom. Relationships are shaped in the space and time of instruction, but also expand beyond the boundaries of classroom space/time (Nespor, 1994). The course network, then, is composed of relationships that are durable and transportable. For example,

the ties that students develop in a classroom because of small group work or peer teaching can carry over into other social contexts, including residence halls and student organizations. Ties formed in those contexts may also carry over to the classroom environment. Illustrating individual behaviors within the boundaries of the social context and the social network allows researchers to identify sources of variation. Learning analytics data, which captures exponentially large observations of student behavior, also allows researchers to identify substantial variance in behavioral engagement relatively efficiently.

Learning Analytics. Learning analytics approaches build on the affordances of “big data” about learners, their behaviors, and their contexts. Big data refers to the collection of information about learners on an unprecedented scale, where every action and interaction in a technology is recorded and made available to the researcher. The current approach to studying course resource use doesn’t sufficiently capitalize on the affordance of learning analytics data. It too frequently treats students as independent agents, liberated from context, community, and instructional practices (Gašević, Dawson, Rogers, & Gasevic, 2016). Student learning is deeply connected to instructional practices (intentional or otherwise) and the classroom (and potentially other) community connections through which meaning making is co-constructed (Palinscar & Brown, 1984). Both theoretically and methodologically scholars now can study student learning as a networked activity of resource use—what has been termed network analysis of social learning (Ferguson & Shum, 2014).

In network analysis of social learning, the focus on social ties, roles, and network evolution in social network methods is applied to formal and informal learning contexts. Research thus focuses on actors, relations, and the development and maintenance of network positions that may support learning. Within the broad umbrella of network analysis of social learning is an approach referred to as social network learning analytics (SNLA) where data from technological tools is used

to supplement the analysis of learning networks. SNLA is ideally suited for analysis of social and technological resource use, “identifying and, where appropriate, strengthening and developing indirect relationships between people, which are characterized by the ways in which they interact with the same [technological object]” (Ferguson & Shum, 2014, p.11)

Social network learning analytics can account for the ways that knowledge and learning are facilitated through interaction (Shum & Ferguson, 2012). SNLA builds on advances in learning analytics and the social network perspective to situate learning interactions and learning processes in their social context (Shum & Ferguson, 2012). Using an SNLA approach allows researchers (and eventually instructors and learners) to identify influences on individual learning as well as to document the emergence of a network of students (Shum & Ferguson, 2012). Applying an SNLA approach to different sections of the same lecture course, where different instructional strategies are already in use, could shed some light on how classroom learning communities emerge because of instructional arrangements, what impact social interactions have on learner performance, and what combination of out-of-class study group participation and digital technological learning resources students are using as they engage in course-work.

For example, Dawson (2010) proposed an innovative model for visualizing and analyzing learner interactions in digital spaces. Building on prior work that established a relationship between a students’ social network position and their sense of community (Dawson, 2006) as well as a relationship between the complexity of a student’s network and their ultimate academic performance (Dawson, 2008), Dawson employed learner data from a learning management system (LMS) to explore the network composition of high- and low-performing learners in an online course. High-performing learners (defined as the top 10% of students by final course grade) had more learner interactions (and more social ties) in online discussion forums than low-performing learners (the bottom 10%). Students also tended to form social ties with peers of equal academic ability.

Dawson's analysis and visualizations presents a promising model of how SNLA could document the emergence of a network of students in an online course. This research would extend that model to face-to-face courses. This project also adds to the research using SNLA by addressing the co-evolution of behavior and social networks in a classroom.

Research Context

Three lecture sections of the same physics introductory course in a single university are the focus of this study. The different instructional approaches in each section have the potential to foster different peer interactions and instructional resource use over time, which in turn and when combined, produce variations in academic performance. For example, instructors who encourage high levels of peer interaction may foster an in-classroom network with numerous peer connections; an instructor who delivers less interactive course designs might encourage fewer peer connections.

The course in this study composed of three sections, each led by an instructor who uses a shared mechanics curriculum, but who has the latitude to make decisions about how to teach the course materials. Among the three sections, instructors in-class A and B rely extensively on the use of clickers to assess student understanding and comprehension of material. The instructor in-class A also has students engage in virtual Python programming³ exercises to visualize abstract physical phenomena. The instructor in-class C uses a more traditional lecture approach during class time. Table 2 below offers some more detail about the three lecture sections.

³ Using the programming language Python, students write code that simulates physical phenomenon. When executed the code provides a visualization, for example an arc of a ball flying through the air, as well as mathematical output that describes the arc of the ball using mathematic notation.

Table 2. Instructional activities and assessments varied substantially by class.

	Class A	Class B	Class C
Instructional Materials	Curriculum, exams, and instructional technology are shared across all three sections		
Course Design	Flipped /Peer Instruction	Flipped/Peer Instruction	Traditional Lecture
Pre-Lecture preparation	Pre-Lecture video by instructor	Pre-lecture video from Flip It Physics	NA
Class Time	Peer instruction w/ practice analytical and conceptual problems; Weekly Python lab in different lecture hall	Peer instruction w/ practice analytical and conceptual problems	Traditional lecture with occasional practice problem completed in groups
Homework	Digital homework system provided through online textbook		

The study population will be comprised of all undergraduate students enrolled in three concurrent lecture sections of the course. This is the introductory course for engineering majors (two other courses at the institution cover similar material but are aimed at different audiences). Per the course catalogue:

The traditional course offers an introduction to classical mechanics, the physics of motion. Topics include: vectors, linear motion, projectiles, relative velocity and acceleration, circular motion, Newton's laws, particle dynamics, work and energy, linear momentum, torque, angular momentum, gravitation, planetary motion, fluid statics and dynamics, simple harmonic motion, waves and sound.

Each section typically enrolls between 200 and 250 students. The course is a requirement for physics, engineering, and material science majors. Engineering majors are also required to take the lab component, however concurrent enrollment is not required. About 95% of the students in each semester take the lab concurrent with the lecture course (ART, 2016).

Study Sample. The course in this study is not representative of the institution of which it is a part. Yet, it reflects the structural inequality common in science and engineering fields. Women, Black, and Latinx students are underrepresented in the course relative to their enrollment in the institution (and their representation in society). Nearly a third of the women enrolled in the course

(43 out of 157) were in the college of Liberal Arts and Sciences. Similarly, women accounted for a third of the engineers in the course (114 out of 410; see table 3).

Table 3. Course Enrollment (n=551)			
	Class A (n=151)	Class B (n=176)	Class C (n=221)
Men	69% (106)	73% (129)	70% (156)
Women	31% (47)	27% (47)	30% (65)
API	25% (38)	31% (54)	26% (58)
Black	1% (2)	2% (4)	1.4% (3)
Latinx	7% (11)	4.5% (8)	7.2% (16)
Multi-racial	4% (6)	4% (7)	3.6% (8)
NA/NH	0.7% (1)	0.5% (1)	
Not Indicated	4.6% (7)	1.1% (2)	1.9% (4)
White	58% (88)	56% (100)	59% (132)
International	9.9% (15)	10.2% (18)	5.8% (13)
Survey Response Rate	78%	76%	83%
<i>College</i>			
Literature, Arts, & Sciences	21% (32)	32% (56)	23% (52)
Engineering	79% (121)	68% (120)	76% (169)

For the purposes of this analysis, I group Asian and Pacific Islander students into the broad racial/ethnic category assigned by the institution (API). However, I acknowledge that this broad category contains a diverse group of students with different experiences and issues around institutional access and equity.

As this course focuses on mechanics and is a requirement for undergraduate engineering, most students are enrolled in the college of Engineering. The few students who are enrolled in the Liberal Arts college are primarily physical and earth science majors (or intended majors). Each course section is relatively evenly split between freshman and sophomores. As this course is a requirement for several academic major programs. Students are often encouraged to take the course during the first year (Personal communication, 2016).

Table 4. Student Enrollment by Lecture Section.

	Class A (n=151)	Class B (n=176)	Class C (n=221)
Freshman	60 (39.7%)	82 (46.6%)	95 (43%)
Sophomore	69 (45.7%)	75 (42.6%)	100 (45.2%)
Junior	19 (12.6%)	15 (8.5%)	19 (8.6%)
Senior	3 (1.9%)	3 (1.7%)	4 (1.8%)

While most of the students in the course were majoring in an engineering subdiscipline, there were subtle differences between course requirements that influenced when students chose to take the course (see table 4 for enrollment by year; enrollment by year is defined by number of credits completed and the semester students started their program). A few students in the course had sophomore levels of credits, but were in their first year of school. They were included in the analysis as first year students.). For example, chemical engineers were required to complete two semesters of organic chemistry in their first year. They were discouraged, by their academic advisors and upper-class peers, from taking organic chemistry and introductory physics at the same time. As such, there is a large group of second year chemical engineers in the course (effectively all the second years who passed both sections of organic chemistry) and no first-year chemical engineers. Similarly, students in mechanical engineering were strongly advised to take the introductory sequence in the first year to remain on progress towards their degree. The three mechanical engineers in their second year taking the course had either failed the course the year before (2) or transferred from a community college (1).

Students could enroll in any lab section regardless of their lecture section, with one exception. This allowed the students to meet and potentially collaborate with students across lecture sections. Only one lab was segregated by lecture section (see appendix-A1).

Data Collection

In social network studies of classrooms, learners and their relationships can be characterized in a variety of ways. In this study, I characterize learners in two ways. Students are considered relative to their role (as a student in the classroom) and their relationships (with other students, with

the instructor, and with instructional tools). Relationships are identified using socio-metric data from the survey instrument. I use cognitive and affective scales from the survey to characterize students' motivations and their beliefs about the course and campus community. Finally, learning analytics data are used to operationalize students' interactions with instructional technologies. Behavior, behavioral influences, and network positioning allow me to illustrate the contextual factors that shape student engagement in the course sections and produce variations in academic outcomes net academic ability and preparation.

In the next section, I describe in detail the sources of data that are used to answer each research question. By way of introduction, I note here that to answer my first research question, I use a survey instrument and learning analytics data to identify significant relationships between student performance and their course resource use as mediated by their course engagement. To address my second research question, I also use data from the survey and learning analytics tools as well as data collected during observations to characterize the emergence of the course network as a function of the instructor's strategies and moves. The data collection approach I employ in this study was developed through two pilot studies in physics lectures of increasing size ($n_1=77$, $n_2=120$). The full results from the fall 2014 pilot and the results from the ongoing winter 2016 pilot are available in the appendix of this chapter.

In this section, I review the data collection procedures. I begin with RQ2 as much of the data collection that is specific to this question will also be applied to RQ1.

RQ2: What is the relationship between students' peer interactions, their technological resource usage, and their course learning outcomes?

To answer my second research question, I use data from the student information system, usage data from digital instructional tools, and data from a survey instrument administered twice during the semester.

Student Information System Data. Information about students and their academic preparation are drawn from the University Student Information system, matched on the University unique name that students provide during survey administration. Demographic information includes race/ethnicity, gender, residency status (state and federal), academic classification (freshman, sophomore, etc.), and major program.

Learning Analytics Data. Data about students' use of different instructional technologies are drawn from the user record logs of the tools used by the instructor. The instructional technology in the course provides easily accessible and well-formatted trace data, where each action in a system is automatically recorded and dated by user id.

Practice Problem Website. In the course, students were provided access to a homegrown practice problem website. The site contained a decade's worth of prior exam questions in multiple choice format. Students would log-on to the website using their institutional credentials and select the topic they wished to review. The website would then provide a randomly selected problem from the topic. After the student selects an answer, they are provided with the correct answer and the distribution of how well other users have fared on that problem. This is meant to provide students with some insight into the potential difficulty level of each problem. The site tracks the problems students attempt and which they answer correctly so as not to re-deliver problems the student had successfully completed.

Measures: Practice Problem Website. For the purposes of including practice problem application use, I created a variable that classifies students by their type of practice problem use. To do this, in every weekly period, I summed the number of attempted problems by students in a session, and divided that total by the average number of problems attempted in a session during that week. An ordinal measure with four categories of intensity resulted. Students were:

- Non-users: Attempted at most 1 session. Also includes students who never logged into the website. Completed on average 20 problems.
- Test Reviewers: Attempted at most 5 sessions (mean=3). Completed on average 50 problems in a session.
- Weekly Reviewers: Attempted at most 19 sessions (mean=14). Completed on average 37 problems in a session.
- High-Intensity Users: Attempted on average 19 sessions. Completed on average 64 problems in a session.

I describe practice problem website use in further detail in the next chapter.

Survey Instrument. The survey instrument contains four types of measures: a name generator to identify social ties in the classroom; Likert-like scales for measuring course beliefs and affective academic beliefs; a map of the classroom for students to indicate where they regularly sit during lecture; and socio-demographic questions (including academic preparation, social identities, out-of-class responsibilities, and academic major plans). I describe each measure below, its advantages and limitations, and any modifications I have made.

Name Generator. Most social network surveys use a name generator question to prompt respondents to identify individuals with whom they have relationships of interest to the researcher (Robbins, 2015). Name generators either draw from a roster of identified possible ties, or they allow respondents to draw the names of peers from memory. Researchers generally assess the type of relationship and the size of the potential network when working with aided or unaided recall. Scholars who are examining a large organization need whole network data, and are asking about multiple kinds of relationships often use an organizational roster where respondents can check off the names of individuals with whom they share a tie.

In this study, I use an aided-recall classroom roster as part of the survey (see figure 3). In the pilot study, which relied on a paper survey, I was not able to use an aided-recall classroom roster because I was unable to obtain a course roster at the beginning of the semester. Instead, I asked students to respond to the prompt: “Please identify other students who you 1) study with to prepare for class quizzes and exams, 2) work with on homework assignments, 3) go to for help about this

course.” Happily, I found that students were very effective at identifying their peers by first and last name. The advantage of eliminating the name roster for the paper survey is the space it allowed to ask about different kinds of relationships: advice, friendship, and study partners. The survey for this study was administered through a website, and the flexibility of that software allows me to use an aided-recall roster as well as to ask about multiple types of relationships as I did in Pilot 1.

Figure 3. Aided recall instrument.

First Name

Last Name

For the student you identified:

	Please select the answer that most accurately reflects how you work together on course tasks.		
	I helped my partner more.	We helped each other equally.	My partner helped me more.
<input type="radio"/> <small>#{QID6/ChoiceGroup/SelectedAnswers/1}</small> <input type="radio"/> <small>#{QID6/ChoiceGroup/SelectedAnswers/2}</small>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

For the student you identified, please check all the boxes that are relevant for your relationship.

- Knew before course
- Work on homework together
- Study for exams together

Would you like to add an additional student?

Yes

For the study, I asked students to identify who they worked with, whether they knew each other before the course, worked on homework together, studied for exams together, and (for Peer Instruction classes) whether they worked on in-class questions.

Measures: Classroom and School Community Index. As discussed in my literature review, one of the challenges of exploring classroom engagement (Kahu, 2013) is to disentangle the influence of campus community from classroom community. Most research on student engagement collapses each classroom community into the larger construct of campus life or sense of belonging. To identify the influence of students’ emotional beliefs about these different communities on their course engagement and performance, Rovai developed a measure of community connection that

differentiates between classroom and campus communities as well as social and academic communities. Recognizing the context dependent nature of community and belonging, Rovai drew items from his own classroom community scale (2002), the campus atmosphere scale developed by Lounsbury and DeNeui (1995) and the Dean Alienation scale (1961) to understand students' psychological sense of community and its relationship to academic performance. The instrument was developed and validated using samples of K-12, undergraduate, and graduate students split between traditional face-to-face instruction and online only instruction. The instrument Rovai developed is designed to measure student community at both the school-level and classroom-level and to distinguish between social communities and learning communities at those levels. It consists of four scales that assess 1) classroom social community, 2) classroom learning community, 3) school social community, and 4) school learning community. The first two scales are part of the "classroom form," and the last two comprise the "school form."

Table 5. Cronbach's Alpha Consistency

Cronbach's Alpha	Internal Consistency
$a \geq 0.9$	Excellent
$0.9 > a \geq 0.8$	Good
$0.8 > a \geq 0.7$	Acceptable
$0.7 > a \geq 0.6$	Questionable
$0.6 > a \geq 0.5$	Poor
$0.5 > a$	Unacceptable

Rovai's Classroom School Community Index (CSCI) performed well on tests of internal consistency and reliability. Reliabilities for the two forms were high: the school form had a Cronbach's α of 0.83 and the classroom form α was 0.84. The internal consistency coefficients for the classroom form: 0.9 for the social community scale and 0.87 for the learning community scale. For the school form, the social community scale had an internal consistency coefficient of 0.85 and learning community scale scored 0.82, suggesting that the items on each scale were generally

consistent across measures. The stability estimate for each form was .91, which suggests scales are likely to be consistent over time.

Table 6. Classroom School Community Index (Rovai et al., 2004)
Classroom Form $\alpha=.83$

Social Community (ICC=0.9)	I feel that students in this course care about each other.
	I feel connected to others in this course
	I trust others in this course.
	I feel that I can rely on others in this course.
	I feel confident that others will support me in this course.
Academic Community (ICC=0.87)	I feel that I receive timely feedback in this course
	I feel that this course results in only modest learning
	I feel that I am given ample opportunities to learn in this course.
	I feel that my educational needs are not being met in this course.
	I feel that this course does not promote a desire to learn.

School Form $\alpha=0.86$

Social Community (ICC=0.82)	I have friends at this school that I can tell anything.
	I feel that I matter to others at this school.
	I feel close to other at this school.
	I regularly talk to others at this school about personal matters.
	I feel that I rely on others at this school.
Academic Community (ICC=0.85)	I feel that this school satisfies my educational goals
	I feel that this school gives me ample opportunity to learn.
	I feel that this school does not promote a desire to learn.
	I share the educational values of others at this school.
	I am satisfied with my learning at this school.

ICC= Internal consistency coefficient

I used both the classroom and the school community scales in my second pilot study. All the items from the CSCI were included in both survey administrations. In the survey administration, I changed the references to school to the name of the institution.

Table 7. Expectancy Value Measures for STEM majors ($\alpha=0.85$) (Perez et al., 2014)

Competency Beliefs	Compared to other students, how well do you expect to do in this course? (5-point scale where 1= Much worse and 5= Much Better)
	If you were to order all of the students in this class from the worst to the best in science, where would you put yourself? (Top 5%-Bottom 25%, five options)
Attainment Value	Is the amount of effort it will take to do well in this class worthwhile to you? (7-point scale where 1 = Not at all worthwhile and 7 =Very worthwhile)
	I feel that, to me, being good at solving problems, which involve science or reasoning scientifically is: (7-point scale where 1= Not all important and 7= Very important)
	How important is it to you to get a good grade in this class? (7-point scale where 1= Not all important and 7= Very important)
Intrinsic Value	In general, I find working on assignments/studying for this class: (7-point scale where 1=Very boring and 7=Very interesting)
	The lectures I attend for this class are: (7-point scale where 1=Very Boring and 7= Very Interesting)
Utility Value	How useful is this class for what you want to do after you graduate and go to work? (7-point scale where 1=Not at all useful and 7= Very useful)
	How useful is what you learn in this class for your daily life outside school? (7-point scale where 1=Not at all useful and 7= Very useful)
	Considering what I want to do with my life, taking this class is just not worth the effort (7-point scale where 1 = Strongly disagree and 7 = Strongly agree)
Perceived Cost	I worry that this class will take time away from other activities that I want to pursue. (7-point scale where 1 = Strongly disagree and 7 = Strongly agree)
	I would be embarrassed if I found that my work in this class was inferior to that of my peers (7-point scale where 1 = Strongly disagree and 7 = Strongly agree)
	I'm concerned that the time I dedicate to this class may affect important relationships in my life (7-point scale where 1 = Strongly disagree and 7 = Strongly agree)

Measures: Expectancy-Value-Cost Scale for STEM majors. In this study, I focus on motivation as an antecedent of academic performance that catalyzes students' use of different learning resources. Eccles' expectancy value theory of motivation (EVT) is supported by a substantial literature validating the ability of Eccles' constructs to predict achievement-oriented behavior (Eccles, 2015). In a study of science, technology, engineering, and math majors' decisions to persist in their major

fields, Perez, Cromley, and Kaplan (2014) adapted Eccles’ instrument to focus on STEM course-work by altering Eccles’ language slightly to address “science related” courses and major programs. In the current instrument, I use the five items Eccles and Wigfield (1995) identified for competence beliefs, the seven items they identified for assessing three different subjective values (attainment, intrinsic, and utility) and three items for perceived cost that Perez et al. (2014) developed; although in all cases I use language from the Perez et al. study. In the Perez et al. study, all the measures had high internal consistencies between 0.75-0.91 (although the individual values were not reported for each scale, only the general ranges I report here). I included these measures in the pilot instrument. The Expectancy Value (EVI) scale had a Cronbach’s α of .85 for both waves.

Table 8. Additional Questions

Demographics	Undergraduate class year
	Gender
	Race/Ethnicity
	On average, how many hours a week do you work on or off campus: _____ hours (Open response, item created by author)
Goals	What is your desired grade for this course? (Open response item)
	What is your intended major? (Open response item)
Academic Preparation	What is the highest level of Math course-work you have completed? (Five item scale where 1=Pre-algebra and 5=Calculus 2 or higher; students are also provided an open response option to list courses not included)
	What other course-work in Physics have you completed? (Eight item scale where 1=No Physics and 8=University of Michigan Courses; students are also provided an open response option to list courses not included)
Proximity/Propinquity	Where do you generally sit during lectures in this classroom? (Students will place an X on a map of the classroom, divided into quadrants).

Course Engagement Influence Questions. I include several additional questions to explore students’ course-work engagement. These include questions that ask about competing demands on students’ time, and their academic preparation for physics. I also include a question about where students sit in the class to understand the influence of proximity on students’ network connections.

Survey Development. In two pilot studies, I used different versions of the survey instrument to understand students' beliefs about the course, their preferences for learning, and their collaborative behaviors. I describe what I learned from each pilot study below.

Fall 2014 Pilot Survey. For the first pilot study, the survey was administered outside of class time through e-mail using the Qualtrics platform. Students were queried about who they collaborate with, how they prefer instruction to be delivered, and what instructional technologies they use in the course. To understand student motivation, I used the Self-Regulation subscale from the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, 1991). The MSLQ takes a cognitive view of engagement, but it focuses perhaps too much on what students do rather than why they do it for the purposes of this study. In the subsequent pilot the MSLQ was replaced by the EVT scale. I also included questions about what technologies students used in the class. The response rate for the survey was 71% (n=51), although that survey pulled in all enrolled students through reported social ties. All students were accounted for in reported ties and these ties were cross-referenced during the observations. I could do this because of the smaller size of the classroom. In the current study, I aim for 75% of students to complete the survey, as this is the generally accepted standard in social network research for approximating a whole network (Robins, 2015). Students who completed the survey were entered into a raffle for a \$50 gift card from Amazon.com.

As part of the social network prompt, students were asked to include up to four collaborators, although if they inputted four collaborators the survey software prompted them to add more contacts if they desired. Students could also report that they preferred to work alone. In general, the unprompted recall method I used generated accurate names, and the socio-matrix was easy to construct.

Several important changes resulted from the pilot study. First, I recognized the paramount need to control for, and understand, the role of physical proximity of individuals and pre-existing

relationships between students. I did not address these in my initial survey, but my subsequent (and more thorough) review of the literature on social networks in educational contexts indicates their importance. Two focus groups conducted with undergraduates (natural science and engineering majors) enrolled in large lectures in the natural sciences in fall 2015 reinforced the importance of capturing information about physical proximity (which I will determine by having respondents identify where on a seating chart of the room they sat) and of assisted recall of peers (which I will address by including a preferred name roster in the survey).

Second, the need for multiple waves of social network data collection became clear once I attempted to analyze the socio-metric data from the pilot study. To make arguments about the influence of the network on students' behaviors, I needed data about changes in the network over time.

Winter 2016 pilot. In winter term 2016, I conducted a second pilot using the revised instrument in one section of an introductory physics course of comparable size at another U-M campus. The first survey administration was conducted in early February before the first exam in the course. The second wave of data was collected the second week in March. Out of 120 enrolled students, 100 attend the lecture on a regular basis and 94 completed the first and second surveys. In the Winter 2016 pilot I also asked questions about how many hours per week students commuted to campus as the study was conducted at a non-residential institution.

As students do not generally bring laptops to the course, the survey was administered on paper. The survey instrument provided space in the margins and at the end of the survey to ask questions about items and provide feedback. As part of the survey instructions I provided to students at the beginning of class, I encouraged them to write notes in the margins of the instrument or to provide feedback about questions through the survey.

Students made two suggestions for improvement. The first suggestion focused on the question requesting information on race/ethnicity. Students suggested the inclusion of more categories and an open response option. The institution enrolls many Arabic and Arab-American students who indicated that they could not accurately characterize their identities given the options provided. Second, the students wanted more information about why they were providing the names of students they collaborate with. I will incorporate this feedback into the final survey instrument.

Survey Administration. The survey instrument was administered twice. Each survey was administered over the web to students through their institutional email address. The survey was open a week before the first and third exams, and closed the day before exams. Students received a 1% bonus on their final grade for completing both surveys (or half a point for only completing one survey). The survey was administered through the Qualtrics web platform. Students who had not completed the survey received a reminder encouraging them to complete the survey 72 hours before the survey closed. This allowed students to develop a study strategy in the first period before they had received feedback about their exam performance, and to (potentially) revise those strategies before the administration of the second survey.

Table 9. Survey Administration.

	Survey 1	Survey 2
Class A (n=150)	138 (92%)	124 (82%)
Class B (n=172)	134 (77%)	120 (69%)
Class C (n=220)	178 (80%)	170 (77%)
Average (n=551)	450 (81%)	414 (75%)

As illustrated in Table 9, there is some substantial variation among classes and between survey waves in completion rates. Through a logistic regression, I calculated the probability that students would not complete one of the surveys. Controlling for gender, race, year in college, and the class a student was enrolled in, Men had slightly higher odds of being non-completers (survey 1=1.08 and survey 2=1.10; values are in odds ratio). Students in class B had slightly lower odds of

not completing survey 1 when compared to students in class A (OR=1.08). No other factors were statistically significant.

Much of the data collected for RQ2 will, through data analysis, also be applied to answering RQ1; namely, learning analytics data, socio-metric data from the survey, and data from the student information system. Additionally, I will use observations of instruction and a qualitative coding approach to characterize the instructional system.

Instructional Observations

I engaged in regular observations of in-class instruction. The course met four times each week, and I attended at least twice a week for most of the semester, although more often three to four times a week. On observation days, I attended at least two of the lecture sections. Each lecture section is in the same room. For both pilot studies, I used this approach to characterize classroom instruction and to provide a richer sense of how students interact in the classroom. These observations are recorded as unstructured field notes (Emerson, Fretz, & Shaw, 1999) collected on a laptop (when appropriate) or through reconstruction from hand-written notes after the observation.

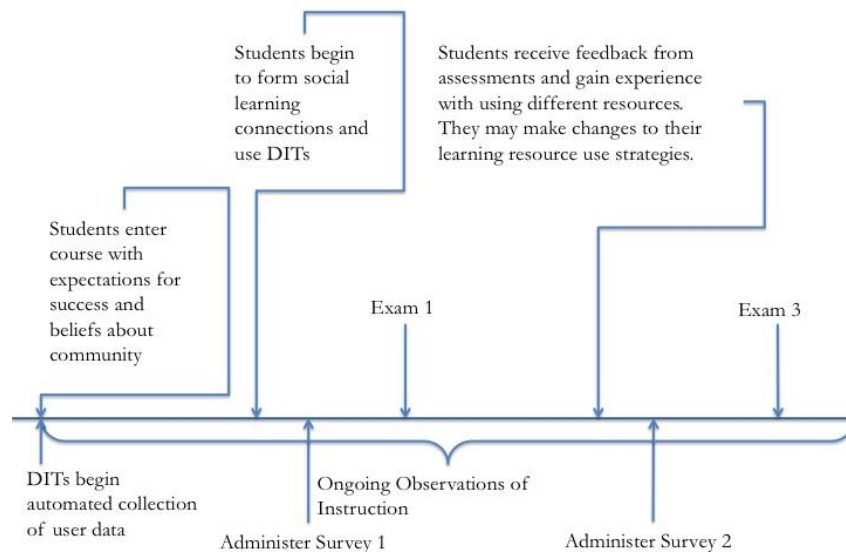
During my observations, I paid specific attention to instructions from the instructor. What are the instructors telling students to do -- both during instructional activities and outside of the class to prepare for assessments? Are students encouraged to talk to each other, solve problems collaboratively, and potentially develop social ties? Or is information delivered through lecture with little to no student interaction? Are students encouraged to use digital instruction tools? Collecting data about the different messages and strategies that instructors use in the course allows me to offer explanations for differences in network structure and student engagement.

Weekly, I would review field notes and write a reflective memo contrasting the instructional approaches I observed. The memos focused on what instructors did in the class, how students participated (or did not) during class time, and what instructors were saying about how students

should spend their time outside of class to prepare for class. I looked specifically for data that disconfirmed my developing ideas about how the course operates, to challenge my developing perceptions.

Data Collection Timeline. In this study, I conceptualize course engagement as an iterative developmental process, shaped by students' pre-existing beliefs and the instructional system. Accordingly, I will capture data at various points during the course to understand how engagement changes throughout the semester. As illustrated in figure 4, observations of instruction began at the start of the semester and continued at least twice a week for each lecture section. Learning analytics data was provided by the institution after the final grades had been submitted.

Figure 4. Data Collection Timeline



Data Analysis

In this section, I propose an analytical approach for each research question, including the data that will be employed for analysis and the potential significant relationships I hope to observe. Where relevant, I include formulas that are appropriate or broad analytical categories.

Before I can address my first two research questions using statistical network analytics, I first needed to identify the classroom-level network of connections among students. To do this, I developed a socio-matrix of directed ties (where student A sends a tie to student B equaling a value of 1, and student B may or may not return the tie). Using the socio-matrix I could identify basic network statistics like density (or the frequency of ties out of total possible ties) and reciprocity (or the probability that any individual will return a tie that is sent to them). Visualizations and network statistics are produced using the statnet package for R (Handcock, Hunter, Butts, Goodreau, & Morris, 2008).

Defining the Network. The network boundary is defined as students enrolled in one of the three sections of Physics 140 in the week before first exam. In network parlance, these students are referred to as nodes. There are 550 students in the network, although not all students completed the course. Students are part of the network whether they reported relationships or not, because there is the potential for them to have relationships with other students. Despite distributing the survey after the add/drop date, it was possible for students who completed the first exam and performed poorly to transfer to a “preparation course”. As such, it is possible for these students to depart the network between the two survey administration periods. These students are accounted for in the estimation procedures, as RSienna allows for individuals to be ‘hard coded’ as leavers. They are identified in the second socio-matrix as exiting the network. This means that there is not the potential for their relationships to persist given the parameters of the network. As such, they are not included in the probability estimation for the second phase of the network. Very few students ($n=5$) left the course.

Students identified who they worked with by completing the network prompt question. The students they identified are referred to as Receivers. Students were defined as Receivers if they were identified by a node as someone who the node worked with to either (1) prepare for lecture, (2) complete homework assignments, or (3) review for exams.

Data Analysis for RQ1.

RQ1: What is the relationship between students' peer interactions, their technological resource usage, and their academic performance in the course?

To address this question, I calculate two analytical models. First, I employ Stochastic Actor Based Modeling to identify the relationships among students' behavioral engagement with social and technological resources. This approach allows for the estimation of two dependent variables (peer collaboration and practice problem website use), using the observed network as a constraint for estimating the probability of changes in behavior also observed in the data. Next, I use the significant relationships identified in the SABM to develop a fixed effects linear regression model. The fixed effects model holds constant time invariant factors, allowing the researcher to hone in on significant relationships related to changes in the outcome variable (in this case, final grade out of 100 points).

Stochastic Actor Based Modeling (SABM). To answer my first research question, I employ the statistical analysis of network models (specifically Stochastic Actor Based Modeling; SABM). I do this to understand the relationships among network ties (i.e., social resources), student attributes (socio-demographics, experience variables, and initial scores on the CSCI Index), and use of the digital instructional technology. SABM is ideally suited to uncover change processes in a network; specifically, how actors change their relationships over time, and how changes in those relationships might be related to changes in the attributes of those actors (their beliefs, their behaviors, their network positioning; Snijders et al., 2010). In a course where students have access to a variety of resources, changes between resource use strategies at time 1 and time 2 might provide substantial insight into differences in outcomes at time 3.

Stochastic models are well equipped to handle longitudinal or panel data where there are multiple waves of data about social ties and actor behavior (2010). SABM requires a reasonable

amount of change among phases of the network. Change is measured by the Jaccard Index, where the distance among successive networks is measured through the number of relationships that change between observations. The Jaccard Index is 0.333 which suggests a sufficient rate of change between the two periods in the network to estimate using SABM (above 0.3 is very good; Ripley et al., 2017, p. 20).

There are six additional assumptions that researchers must address to be able to appropriately apply SABM analysis.

SABM assumptions. The first two assumptions of SABM relate to how time is conceptualized in the data collection process. First, time in the model is treated as continuous (Snijders et al., 2010). Data must be collected at least twice, creating network panel waves. Second, the changes observed in the network are the byproduct of an interaction either among individuals or between an individual and a resource (Snijders et al., 2010). The network is assumed to be the result of a Markov Process, where “for any point in time, the current state of the network determines probabilistically its further evolution, and there are no additional effects of the earlier past” (p.4). That is, network two is a byproduct of network one, and changes that predict the estimation of network two could only arise from the configuration of network one. Any information that is relevant to the network structure is assumed to be captured by the current state of the network. Both assumptions are met in the current study, to the extent that they can be. It is, admittedly, a limitation that the researcher cannot know unknowns related to network structure.

The next two assumptions relate to how SABM considers actors and agency. In SABM, individuals control with whom they connect (by, in social network parlance, sending an outgoing tie). In a classroom where students are consistently assigned and re-assigned to new groups by an instructor, SABM would be an inappropriate analytical approach. However, SABM is well suited to studying how students make choices among potential social ties. Similarly, the second assumption

related to agency in SABM requires that at any moment in the timespan, an individual actor has the opportunity and ability to change an outgoing tie. Classrooms where students are permitted to select study groups, but also required to maintain their groups over time, would not be well suited to SABM because of the lack of agency and the lack of change. Both assumptions are met in the current study.

The final two assumptions relate to how SABM treats change. First, the evolution of the social network is a process of change determination, where changes in sending ties are influenced by the network position of actors (their centrality or popularity) as well as the attributes of an actor (sex, race, socioeconomic status). Second, changes to outgoing ties are also influenced by the position and attributes of other actors in the network, such that actor A's decision to connect to actor B might be based on B's positioning (e.g., popularity) and attributes. Both assumptions are met in the current study.

Estimating results. For each individual student, weights are calculated for each parameter given the probability that the network configuration at time one would result in the network at time two. These weights are calculated through the objective function. The structural equation for SABM is referred to as the objective function as it represents the net value each focal actor would assign to the network given their preferences and the structure of the network (Snijders et al., 2010). The objective function is used to calculate the probability of change in the network based on the possible states of an actor (their ties and values of the covariates; Caimo & Friel, 2010). The objective function in its general form:

$$f_i(\beta, x) = \sum_k \beta_k S_{ki}(x) \quad (1)$$

In this model, i refers to the ego or focal actor; k refers to the time-period, and x denotes each individual covariate held constant in the estimation procedure (e.g. race, gender, academic major program, etc.). The function $f_i(\beta, x) = \sum_k$ is the summed value for focal actor i , dependent upon

the state of the network at each time interval. This function describes the utility that an individual will find given different configurations of the network and levels of behavioral engagement, given their observed preferences in the data. The function $S_{ki}(x)$ refers to a vector of effects (in SABM parlance; also covariates) stemming from the behavior of the focal actor, as well as his network positioning and the behaviors of his network partners (these factors are chosen based on theory and prior research). β_k refers to the strengths of each effect on behavior choices—in this study, the decision to add, maintain or end a study relationship or to increase, decrease, or maintain use of the practice problem website (Snijders, Van de Bunt, & Steglich, 2010, p. 29). The statistical parameters notated by β_k , which are described in Table 10 below, report the probability that the corresponding network statistic will “have an impact on the network dynamics, and vice versa if the value of the parameter is negative” (Caimo & Friel, 2014, p. 12). That is, parameters greater than zero suggest that the parameter has an increasing influence. For example, if the mutual/reciprocity term is greater than zero, relationships that are mutual have higher probabilities of persisting. Similarly, if a receiver term for women is greater than zero, then women have a higher probability of sending a tie (or identifying a relationship with another student). The converse is true for negative terms. If the sender term is below zero, then women have a decreasing probability of sending a tie.

The SABM algorithm in R, using the RSIENA package, cycles through four estimation procedures to converge on a set of results: method of moments (Snijders, 2001; Snijders et al., 2007), Generalized Method of Moments (“GMoM”; Amati et al., 2015); Maximum Likelihood (“ML”; Snijders et al., 2010a); and Bayesian estimation (Koskinen, 2004; Koskinen and Snijders, 2007; Schweinberger and Snijders, 2007). This is accomplished through a Markov chain process where the “probability of future states given the present state does not depend upon past states” (Caimo & Friel, 2014, p. 9). The methods of moments procedure begins by selecting starting parameters from

the observed values, and determining “the parameter estimate value for which the expected values...equals the observed values” (Caimo & Friel, 2014, p. 14).

Changes in either behavior or relationships are a function of the probability of the new network configuration that would result. Of the estimation procedure for the objective function:

The probability that an actor makes a specific change is proportional to the exponential transformation of the objective function of the new network, that would be obtained as the consequence of making this change....[The formula for the objective function, see above] are the same formulae as used in multinomial logistic regression (Snijders, van de Bunt, & Steglich, 2010, p. 38).

The results are similar to pairwise logistic regression, with the expectation that the probability of a tie between two pairs is dependent upon the structure of the network at the time of each survey administration. Two individuals with no other ties will result in one probability estimate, while two individuals with many other shared relationships in common will produce a different probability estimate. These results are reported in log-odds.

For each estimation procedure, the algorithm repeats simulations of the change observed in the network data and in the co-evolving behavior. At the end of the process, this outputs three types of estimates. First, a rate parameter of change for the network and for the behavioral variable are estimated. The rate parameter of change identifies the unobserved (or simulated) number of opportunities each individual has to make changes to their relationships and/or their behavior. Referred to as steps, individuals are presumed to have, on average, some estimated number of opportunities to choose to change (or not) and that those (taken or not taken) steps result in the observed changes in the second time-period. For example, a student with five study partners has, in absolute terms, five choices to make about maintaining or ending those relationships in the second time-period. A student with no study partners has no choices to make regarding maintain or eliminating relationships. Both students might have, on average, two opportunities to add to their network in the next time-period, even if the student with multiple existing relationships is better

situated to capitalize on their relationships to find new study partners. Their choices are constrained by the (potential) need to maintain existing relationships and by the size of the network, which may not support large study groups, as well as the overall trend regarding relationship formation or dissolution in the network. Still, a dissolving network might result in the same number of estimated steps as an expanding network.

Table 10. SABM Model Terms	
<i>Behavioral Terms</i>	
<i>Linear Behavioral Term</i>	Similar to the dependent variable in a linear regression. For the practice problem website use outcome, estimates the log-odds that a student would increase their practice problem website use between the two survey periods. (Non-User to High Intensity User; range of 1 to 4). For the academic performance outcome, estimates the log-odds that a student would improve their final letter grade between the two survey periods (F-A; range from 1 to 5).
<i>Quadratic behavioral term</i>	Similar to the quadratic term in a linear regression.
<i>Practice Problem Website Use Terms</i>	
<i>Isolate</i>	Binary term for whether a student works independently (1) or reports collaborators (0).
<i>Average Practice Problem Website Use of Peers</i>	accounts for the average intensity use of peers (Non-User to High Intensity User; range of 1 to 4, 0 if no connected peers)
<i>Effect from Technological Proficiency</i>	Student response to the technological proficiency question on the survey (1-7, Strongly Agree to Strongly Disagree “I have the technological skills I need to be successful in this course).

The estimation procedure also produces a set of coefficients for structural network effects, influences on sending and receiving relationship nominations, and influences on changes to behavior (e.g. practice problem website use). In general, a well fit model will have a t-ratio for convergence

for each covariate that is below 0.1 and below 0.25 for the whole model. All the covariates and the model were well below these thresholds. Table 11 includes model terms and a brief description of each.

Table 11. Structural Network Effects.

<i>Outdegree (density)</i>	Binary term for each relationship that an individual sends in the network (1-relationship reported, 0-no relationship).
<i>Reciprocity/Mutual</i>	Whether a relationship is reported by both students.
<i>Transitive Triplets</i>	<i>Transitive triplets</i> - Number of shared relationships between each pair of students (often referred to as the friend of my friend is my friend principle)
<i>3-cycles</i>	Number of closed cliques where all individuals are connected to each other. Individuals in 3-cycles tend to be more susceptible to social influence (e.g. Cheadle & Schwadle, 2012).
<i>Indegree popularity</i>	Number of relationship nominations a student receives
<i>Indegree activity</i>	Number of changes in relationships a student receives between the two time-periods
<i>Outdegree activity</i>	Number of changes in relationships a student reports between the two time-periods
<i>Sender</i>	Probability that an individual would report a collaboration given some marker (e.g. gender, response to a survey question)
<i>Receiver</i>	Probability that an individual would receive a collaboration from another individual in the network given some marker (e.g. gender, response to a survey question)
<i>Homophily</i>	Probability that a tie will occur between two individuals with the same categorical value.
<i>Similarity</i>	Probability that a tie will occur between two individuals with the same value on a continuous scale.

Structural network effects are estimated only using the observed network, and not the co-evolving behavioral mechanisms as opposed to the terms described above. These ‘effects’ account for the influence of network structure on network evolution. For example, the outdegree term is a

binary for whether an individual report a relationship with each potential individual in the network. Reciprocity/mutual effect, in contrast, is defined by the number of reciprocated ties an individual possesses. Structural network effects are only interpreted in terms of the network. The reciprocal effect, when positive, suggests that a relationship will maintain. A positive outdegree parameter suggests that individuals are not selective in their relationships.

By calculating both the rate of change and the probability of a tie being formed in the presence of different network positions and actor attributes, SABM allows researchers to understand how structure and interdependence in social relationships can evolve over time. The network is presumed to co-evolve as a function of social connection and behavioral choices. This approach allows for the examination of social influence and social selection (Dokuka, Valeeva, & Yudkevich, 2015). Students might adopt the behavior of peers they are similar to, or they may seek out peers with similar behavioral strategies.

Influence and Selection Tables. One advantage of the SABM approach is the ability to calculate versions of the objective function that estimate probabilities for selection (given an attribute) and influence (given connection and variation in behavior). In this study, I calculate selection tables identifying the probability that students who share an identity would report a relationship in contrast to students who do not share an identity (e.g. women vs men, domestic vs international).

Selection tables sum the parameter for sender probability and receiver probability:

$$\beta_{ego} (v_i - \text{mean}(v)) + \beta_{alter} (v_j - \text{mean}(v))$$

which produces a table with the odds ratio that a sender would report a relationship to a receiver with each condition of the attribute. In this equation, $\beta_{ego} v_i$ refers to the log odds that individual i will send a tie. $\beta_{ego} \text{mean}(v)$ refers to the average log odds that an individual in the network will send

a tie. $\beta_{alter} v_j$ refers to the log odds that an individual i in the network will receive a tie. $\beta_{alter} \text{mean}(v)$ refers to the average log odds that an individual in the network will receive a tie.

Influence tables are slightly more complex, in that they account for the average behavior of peers. The linear and quadratic behavioral terms are included alongside the average similarity in behavior of a student's peers, to account for the behavior of the focal individual (i) and the average behavior of i 's connected peers (j):

$$\Gamma_i^{\text{beh}} = \beta_{\text{behavior}} (z_i - \text{mean}(z)) + \beta_{\text{behavior}} (z_i - \text{mean}(z))^2 + \beta_{\text{average}} (z_i - \text{mean}(z)) (\text{mean}(z_i) - \text{mean}(z))$$

where,

- $\beta_{\text{behavior}} (z_i - \text{mean}(z))$ refers to the linear log odds that an individual's behavior will increase between the two time-periods; and $\beta_{\text{behavior}} z_i$ refers to the individual log odds that i will increase their behavior between the two time periods and $\text{mean}(z)$ refers to the average log odds in the network that an individual will increase their behavior.
- $\beta_{\text{behavior}} (z_i - \text{mean}(z))^2$ refers to the log odds that an individual's behavior will have a non-linear shape; this is the same parameters as above, but squared to account for the non-linearity.
- $\beta_{\text{average}} (z_i - \text{mean}(z)) (\text{mean}(z_i) - \text{mean}(z))$ refers to the log odds of the peers i is connected to engaging in the same level of behavior in each time-period, where $\text{mean}(z_i)$ refers to the average log odds *of the other peers that i is connected to*.

The selection table I report in the next chapter contains the odds ratio that a student at one level of practice problem use at the beginning of the course will adopt the practice problem use intensity of peers at a different level between the first and final exam.

Fixed Effects Linear Model. In this study, I observed substantial evidence that the factor scales related to course beliefs and affective academic beliefs and students' level of behavioral engagement with social and technological resources changed over time during the course. This poses an interesting question. Are changes in beliefs or behavior related to changes in students' academic performance during the course? If they are, if for example increased use of the practice problem website is significantly related to improved academic performance, then productive opportunities for intervention might result.

The fixed effects linear model holds constant all the variance not presumed to change over time. There are two core assumptions of fixed effects linear models. First, a basic fixed effect model assumes no serial correlation—that is, no correlation among effects over time. Second, the model also assumes no cross-section correlation among subjects. I calculated a Hausman test that suggested that the difference in coefficients was not systematic ($p < 0.004$) which allowed me to reject the use of a random effects model ($p < 0.004$).

In the model, I report in the next chapter, the outcome of interest is students' average academic performance out of 100 points. I control for changes in practice problem website use, sense of community, expectations and goals, and changes in the number of collaborators a student reports and receives in each time-period. Based on prior research, I include an interaction for time and gender, as historically women have underperformed in the course (Koester, Gromm, & McKay, 2017). I was interested in exploring if the grade deficit between men and women increased over time. Including women and time in the model improved performance ($F = 3.065^{***}$ vs. 2.52^{**}).

Logic of Inquiry. This study belongs to the tradition of mixed methods research in education. The mix of quantitative and qualitative data collection and analysis in this study builds off Greene's (2007) five primary purposes for mixed methods. First, collecting data through multiple methods allows for the corroboration and correspondence of findings. For example, through observation the researcher may identify salient practices that deter peer interaction which are also reported by students' in the survey. The qualitative observations also address Green's second purpose of complementarity in data, which allows for elaboration, enhancement, and illustration of results from one method with the results from a different (complementary) method. Observational data can provide examples and instances of mechanisms that are suggested by inferential statistical analyses.

In this study, the observational data also serves Greene's final three purposes. Observational data helps to develop the instrumentation of the survey instrument. For example, I changed the language and phrasing of some items in the survey based on observations before administration, to more accurately reflect what instructors were doing. Observational data also served as a counterpoint to the survey data, providing alternative explanations for findings. Finally, the observational data expands the breadth and range of the findings in this study, by providing a rich description of the instructional context, which is often missing from quantitative analyses of post-secondary teaching and learning.

The logic of this inquiry presumes that observations provide rich context for exploring the inferences afforded by the SABM and fixed-linear model analyses. For example, in this study there are three social contexts (or classrooms) across which various forms of instruction are implemented. An approach that simply uses learning analytics and survey data would miss out on the (potentially) important influence of instructional variation. An approach just based on observation would lose out of the affordance of visualizing and quantifying the network structure, and on the (self-reported) data that is available through survey administration. Throughout this study, I have used observations of instruction to inform quantitative data collection and analysis.

Validity of Interpretations and Limitations. Using a variety of methodological traditions potentially introduces different concerns about validity that are related to methodology as well as the selection of the population. I describe some of the limitations associated with each method, and how I attempted to address them as part of my data collection and analysis.

As I have noted above, social networks are limited by the researchers' ability to capture a whole network (Wasserman & Faust, 1994). Although qualitative observations can help to flesh these networks out and potentially identify the ties that students do not report, this is an unavoidable limitation of SNA data. There may be important interactions that impact academic outcomes that

are not captured by the question prompts I employ in the survey network. SNA is also limited by the cognitive mapping of the respondents, such that students may not be effective at identifying their network ties even when provided an explicit prompt.

In this study, I am primarily interested in specific kinds of relationships and interactions. In both pilot studies, when I identified the types of interactions I wanted students to include they were very successful at identifying relationships. In the fall 2014 pilot, for example, I asked students to identify students with whom they collaborated on in and out-of-class assignments. I then cross-referenced these reported relationships with observations. Overall, students identified students with whom I observed them interacting. In fact, only one triad of students was different from their reported relationships, and this was a result of a student in their group of four dropping the class.

In both pilot studies, the classrooms were small enough that I could survey quickly all the students in the room and with whom they were interacting. In this study, my observations will be undertaken in a similar manner, through unstructured note taking. However, my decision not to use a guiding protocol that would train my attention on specific practices increases the potential for bias. Blind spots in my observation might have resulted. I believe that the narrow focus on instructional practices mitigated some of this bias. I also engaged in peer debriefs about what I'm observing with a colleague in the physics department who also sat in on a few classes. During the study, I could periodically chat with students in the class about their perceptions of instruction. Their observations generally accorded with my own. In most cases, their feedback furthered my understanding of what I observed, as opposed to challenging my conclusions.

The analytical modeling process also posed some challenges. Model selection in SABM is driven by theory, but the estimation procedure requires data that has sufficient information to allow for a simulation. The network I describe in the next chapter of this study was particularly sparse, so I needed to fit a model that addressed my theory and was parsimonious. The decreasing number of

network connections may reduce the explanatory value of the model as there are unbalanced outcomes, relative to sparse predictors. For this reason, I included the fixed effects linear model. Adding the second model allowed me to focus on influences that I believed were specific to behavioral engagement with social and technological resources.

One limitation of this study was the challenge involved in modelling race and ethnicity as a predictor of out-of-class study group participation. Students had the option to provide an open-ended response to the race and ethnicity category. For students who fit into the broad institutional category of Asian/Pacific Islander, a whole host of more nuanced and complex identities from across the Asian American diaspora emerged. Collapsing these students into one broad analytical category for modeling purposes was an unfortunate necessity that potentially masks much of the complexity of relationship formation around shared cultural experiences. While students also had an open response for gender, all the respondents identified as either men or women (or male or female). In future work that builds upon qualitative interviews conducted after the data collection I describe above, I will be better able to unpack the multiple intersecting identities that shape students' classroom experiences.

Contributions

The results of this study will unpack the interdependent influences of academic student collaboration and technological resource use on students' academic performance by providing insight into how students' behaviors and their social connections relate to student outcomes. As important, this study will advance learning analytics research by demonstrating a theoretically driven and comprehensive method for collecting and analyzing peer interaction data for student success models. The comprehensive modeling of student course engagement is necessary if we are to improve instructional practices and student learning in science fields.

By developing this more comprehensive approach, the study also contributes to our conceptual understanding of how students become engaged in their course-work in higher education. Studies of student engagement in the field of higher education typically examine engagement at the institutional level; detailed classroom studies are rare and thus implications for instructional practice and theory development are quite limited. My attention to engagement studies in k-12 settings suggests means for expanding our thinking about college student engagement, yet these studies of classroom engagement are limited by researchers' decisions to focus exclusively on the behavioral or psychological influences on student's engagement with their course-work. I believe the conceptual and analytical model that I validate through this study will offer greater predictive and explanatory power than previous models of student course-work engagement. The broad construct of student engagement encompasses a variety of interactions, activities, and involvements that students experience as part of their time in college. To understand the relationship between engagement and important developmental outcomes, we need to specify and situate the forms of engagement in which we are interested. By validating a model of student course-work engagement in large lecture halls this study contributes to the literature on student engagement by providing an example of how this work can be accomplished, and (I hope) points to future directions for how researchers could explore the dynamic process of engagement across campus sub-cultures and social contexts. This study also bridges behavioral, psychological, and instructional approaches by identifying how influences identified in each perspective work together to foster the process of course-based engagement.

Chapter 4: Results

In this study, I identify the relationships among 1) students' collaborative study behavior, 2) their use of a practice problem website, and 3) their course beliefs and affective academic beliefs in a large introductory physics lecture, what I term course-work engagement and its relationship to course grade. This was accomplished through two complementary methods of data collection and analysis. First, I observed instruction throughout the semester in three lecture sections of a course to discern differences in the course structure and practices used by the instructors. Second, I used stochastic actor based modeling (SABM) – a statistical network modeling method that maps changes over time among participants who organized in a defined social context – to estimate the significant relationships among collaborative study behavior, practice problem technology use, and course grades.

In this chapter, I first report the results of my classroom observations with a focus on the similarities and differences among the three lecture sections. These findings illustrate how the instructional system of the course might shape students' course-work engagement, which answers my first research question (research question 1; RQ1). I then report the results of the statistical analysis of changes in study group participation and instructional technology use (SABM) in the course network, which answers part of my second research question (research question 2A; RQ2A). These findings identify the significant relationships among students' participation in collaborative study and their use of the practice problem website. Finally, I report the significant relationship of changes in course beliefs and affective academic beliefs alongside changes in study group participation and practice problem website use to identify significant relationships with improving or

declining course grade, which also addresses part of my second research question (research question 2B; RQ2B).

RQ1: The Instructional System

Instructional Approaches. The classroom environment and the instructional activities vary across the three lecture sections in this course. In this next section, I characterize the similarities and dissimilarities among the three sections to highlight how different aspects of the instructional system can influence students' behavioral engagement in the course. This comparative analysis also highlights how subtle differences in instructional practices might encourage (or deter) different forms of behavioral engagement in course-work. The instructional activity system encompasses the goal oriented artifact mediated practices involved in teaching and learning in the course, distributed among the community of the course.

The three lecture sections in this study shared curriculum, assessments, and instructional technology, but varied in instructional approach and philosophy. The three instructors followed an approach to instruction common in large lectures in American undergraduate higher education (Losh, 2014). The instructors stood at the front of a large lecture hall (200+ seats), using a small microphone clipped to their shirts to project their voice. They projected slides on three screens at the front of the room. Slides were used to share conceptual material and analytical problems. Each instructor developed their own slides.

The instructors were similar in terms of demographics as well. All three were white men with doctoral degrees in physics. The instructor in-class A was a native English speaker, while the instructors in-class B and Class C spoke English as a second language. The instructors in-class A and C were tenured university professor, and the instructor in-class B was a longtime lecturer in the department.

I observed some meaningful differences in their instructional approaches. The instructor in-class A would project information as it was relevant, with information about a problem or concept appearing in sequence on a single slide. The instructor in-class B preferred many slides with less information, bulleted or using simple black on white diagrams. The instructor in-class C used very few slides – sometimes no more than five per class meeting --but included all the needed information on each in detailed paragraphs.

The instructors in-class A and B used a flipped peer instruction model. In this instructional design, students watch a short video lecture before attending class. The instructors in-class A and B used different pre-lecture videos. Students in-class A viewed videos of the instructor completing problems on a YouTube channel and students in-class B purchased a homework system that contained videos produced by a third party. Once in lecture, students in-class A and B completed a series of multiple-choice problems with clickers interspersed during the lecture. Clickers are small plastic remotes that link up to the learning management system and record students' responses to multiple choice question. Each clicker has a few small buttons labeled A/B/C/D for answering multiple choice questions. In contrast, in-class C students listened to about 40-45 minutes of lecture in each class session, and then completed a single multiple-choice problem using the clickers, every other day.

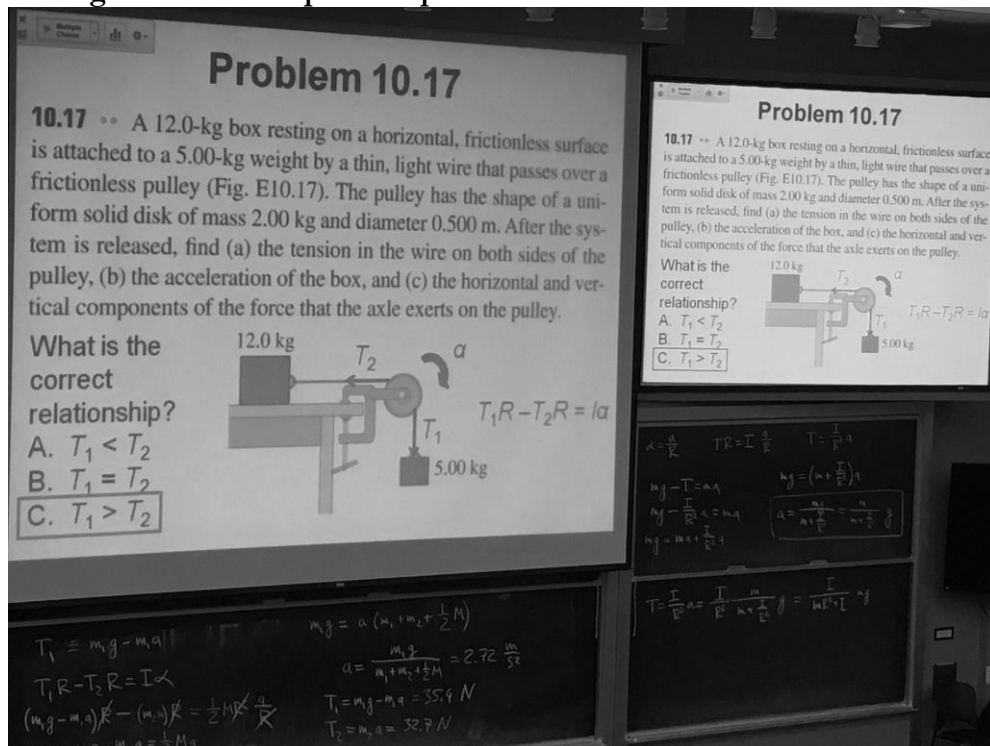
Instructor A typically engaged one or two students in discussion after each problem, asking those students to explain their approach and rationale. My fieldnotes reveal that the instructor in-class B did this much less often, and was more likely to respond to direct questions rather than asking students to participate. The instructor in-class C's approach was to work through a problem and then respond to clarifying questions from students. His back was usually turned towards the students, so if they had questions as he wrote on the board they had to call for his attention. My fieldnotes from week 6 record how this approach tended to discourage student participation:

[Instructor C's] class is the most traditional lecture. He uses questions from the [text]book (that he highlights on the syllabus)... Instructor C goes through the material very quickly because students were not asking questions, although they also had no real opportunity to ask questions. [Class C field notes; Week 6]

I also observed some commonalities in the instructional approaches in these three course sections. As is common in introductory physics classrooms, all three instructors used demonstration units to illustrate physical phenomena. Instructors in-class A and B did this quite often, generally sharing instruments used for demonstrations between class periods. The instructor in-class A often projected a diagram of a concept (e.g. gravity and drag) alongside its physical demonstration. On the rare occasion that these two instructors used different demonstration units, the instructor in-class B was likely to incorporate a dramatic flourish, like shooting a teddy bear with a paint ball gun to demonstrate trajectories. In-class A, problems about a concept always preceded its demonstration, while the instructor in-class B varied this format. The instructor in-class C used demonstration units sparingly, incorporating the demonstration into the problem as he went about solving it.

Another similarity was the use of clickers in all three courses. Instructors in-classes A and B occasionally showed the distribution of students' responses, or the distribution of responses to their homework questions (in-class B). See figure 5 below for an example problem from class B.

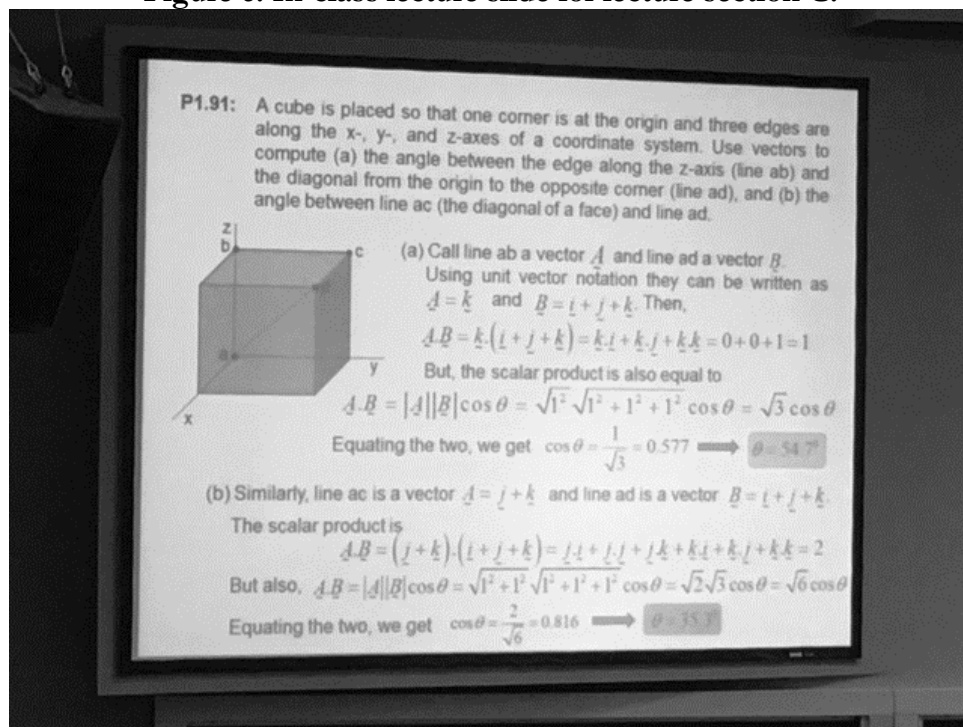
Figure 5. In-class practice problem from lecture section B.



Instructors in-class A and B also regularly checked the distribution of student responses before they closed questions. They would often provide hints, feedback, or additional instruction if too many students entered an incorrect response.

The instructor in-class C, however, provided fewer problems. He would identify for students practice problems in the book that they should review before the next class. One of these problems would be projected for i-clicker credit. Students who completed the problems before class could bring their solutions to class. The instructor in-class C could not figure out the system for displaying results. He often made attempts to share the results with students, but this always resulted in aborted attempts.

Figure 6. In-class lecture slide for lecture section C.



Out-of-class Learning Activities. All three lectures used the same digital homework system that was integrated with the text book. A different instructor who worked with graduate lab assistants coordinated the use of identical lab assignments and lab activities. Lab assignments included a mix of physical experiments and digital simulations using the virtual Python (VPython) programming language. Students would read through a pre-lab guide and complete a short quiz at the start of each lab section.

The instructor in-class A required his students to complete VPython numerical modeling assignments in addition to their lab assignments. Once a week, his course section would meet in a different lecture hall that was equipped with tables for students to work on laptops (which student either brought to class or borrowed from the department) to complete VPython exercises. This resulted in a very different work environment for students:

[Class A] today was very independent. Students were all at different places in the tutorial/assignment and they worked individually or in small groups. [Lecture Hall 2] is more conducive to this, but it's not really set up for discussion. In contrast to the

regular lectures, very few students chatted or shared resources. [Class A field notes; Week 2]

The weekly VPython sessions resulted in less interaction than during Peer Instruction problem solving. During Peer Instruction, students would chat, pass papers back and forth, look over and discuss each other's solutions. This resulted in lots of conversation, the volume of which increased as time passed. In contrast, the VPython sessions were very quiet, and students would rarely lean over to ask their peers a question about a piece of code on their laptop.

In the two classes where students were expected to watch pre-lecture videos, students were afforded opportunities to provide feedback to the instructor about their comprehension of the reviewed material before lecture. Students in-class A were prompted at the end of every video to email the instructor with questions. Students in-class B, who were required to purchase an additional homework system called 'Flip It Physics', answered a homework question identifying the concept they found the most difficult from the pre-lecture video. Flip It Physics allowed the instructor in-class B to deploy clicker questions in the lecture videos that students reviewed before class. Students would complete these questions before they arrived in-class, and the instructor would often review the results of the questions if there was considerable misunderstanding. The instructor in-class B often reviewed this feedback from students during lecture:

Instructor B reviews Flip It Physics quotes from students—he projects them on the slides. ... Instructor B tells students he bases some of his lecture on responses to this question, and that students should take this as an opportunity to give him feedback and to clarify what concepts they need help with [Class B Field Notes; Week 6]

The instructor in-class B included the out-of-class clicker questions in calculating students' final grades in the course. Students in-class C were not required to watch pre-lecture videos, complete pre-lecture questions nor were they assigned additional VPython exercises.

Study Resources. Across the three sections, students had access to several tools and resources for completing assessments and seeking help. For example, each section had an online

forum for ‘anonymous’ question asking where students could post questions about specific homework problems. Although other students responded to these questions, they were more often answered by the undergraduate learning assistants for each course, who would respond to queries during their office hours. Students also used the forum to ask about course business like due dates, the grade curve, and the topics that would be included in an upcoming exam.

These resources could be accessed through the course website, which also included an updated calendar (with links to video lectures and assignment submission portals). The course website was a primary tool for communication. Instructors used the site to message students about course-work. The site also served as a digital gradebook, providing students the results of their learning assessments.

There were also a few face-to-face resources available to students designed to supplement the course. Students could visit the Physics help room where learning assistants and instructors would hold office hours to help with questions from lecture, homework assignments, and exam review. Students could sign up for supplemental instruction through the campus science learning center, where they received small group tutoring from an undergraduate instructor. Space in these groups was limited and enrollments filled up quickly at the beginning of the semester. Engineering students were also able to sign up for practice exam sessions, where an instructor would provide students additional practice exams and practice questions in the lead up to mid-terms and the final. These sessions required registration and were held on the weekend before an exam (see table 12 for a summary of instructional activities and assessment by class section).

Table 12. Instructional activities and assessments varied substantially by class.

	Class A	Class B	Class C
Instructional Materials	Curriculum, exams, and instructional technology are shared across all three sections		
Course Design	Flipped /Peer Instruction	Flipped/Peer Instruction	Traditional Lecture
Lecture Slides	15+ slides a class w/ substantial text	15+ slides w/ less text, more often visualizations	5-7 slides with substantial text
Pre-Lecture preparation	Pre-Lecture video by instructor	Pre-lecture video from Flip It Physics	NA
Class Time	Peer instruction w/ practice analytical and conceptual problems; Weekly Python lab in different lecture hall	Peer instruction w/ practice analytical and conceptual problems	Traditional lecture with occasional practice problem completed in groups
Homework	Digital homework system provided through online textbook		
Out-of-class Activities	Virtual Python Programming exercises	Clicker Qs during Pre-lecture Videos	NA

Encouraging Course-work Engagement

Despite variations in instructional approach, the instructors had relatively similar approaches to encouraging engagement during lecture time. After the first week of the class, the instructors made few references to help seeking or study resources. In the time leading up to and the after an exam, they might direct students to the Physics help room or encourage students to seek out supplemental instruction. Yet, during nearly every class session that involved clickers, the instructors referred to working with peers collaboratively to solve problems. For longer analytical problems, the instructor in-class A would frequently admonish students to “find a partner with an answer different from yours.” The instructor in-class B would tell students to turn to their neighbor and check their work. The instructor in-class C often encouraged students to “find a friend, make a friend”.

Students responded to these admonishments. I regularly observed as conversational chatter rose substantially in response to analytical problems. In fact, the instructors seemed to respond to student body language as much as the clicker software in determining how long to give for an individual problem. If substantial numbers of students were huddled in conversation (bending over

rows of seats, or passing around scratch paper with a solution to neighbors), instructors seemed to provide more time for the problem – even if much of the class had ‘clicked in’ their answer.

These groups appeared to sort themselves largely based on proximity. Students who sat near each other leaned over empty chairs or leaned back to talk to a student in another row. The groups were homogenous to the extent that a class with very few women and students of color would permit. I did not notice substantial social segregation based on visible social identities like gender and race during class time, except for white men. While women, Black, and Latinx students were likely to work in heterogeneous groups with white and Asian men, white men appeared equally likely to work in diverse groups or to segregate into groups composed exclusively of white men. The one exception I observed was a mixed gender group of Asian students who worked together early on in-class C. However, by the end of the first week, as students dropped the class and seats freed up, this group reorganized into smaller heterogeneous groups.

Students appeared to interact in very similar ways across all three classrooms. Engaged conversations happened in the front half of the room, and students in the back half of the room (especially the back two rows) were less likely to confer with their neighbors during my observations. Students in the back half of the room were also more likely to have their laptops out during lecture (something discouraged but not banned by all three instructors). I often observed students in the last few rows entering a problem into web search engines to find solutions. This was particularly common in-class C as the problems came from a widely used textbook.

Although all instructors encouraged students to collaborate in-class, the time and space provided for collaboration varied between classes. Students in-class A had the most time during clicker questions, sometime upwards of ten minutes to review their answers in small groups. Students in-class B were generally provided less time to work through problems, and spent more time on discussing the solution as a large class. Students in-class C were often provided only one

questions every other day. On the days that they completed a question, they were provided about five to seven minutes to work in small groups. As many students had completed the assigned problems outside of class, I often observed students who had the solution explaining their result to student who were working on the solution during class time.

It also is worth noting that the variations in out-of-class learning activities might also produce different forms of course engagement across the three classes. Students in-class A had to spend out-of-class time working through the weekly VPython assignments—time that might otherwise have been spent on other study activities. Similarly, students in-class B had higher levels of accountability for watching the pre-lecture videos as part of their grade was based on their response to i-clicker questions embedded in the videos. Students in-class C were incentivized to work on review problems from the textbook as one of those problems would be used for an in-class for credit assessment.

Synthesis of observation findings. Among the three classes, what constituted engagement varied. In this study, I focus on forms of behavioral engagement shared among the three sections (out-of-class collaboration and practice problem website use). However, a students' tendency to engage might necessarily be influenced by the competing demands on their time that stem from their different instructors. The substantial variation across the three lecture sections suggests that although students are enrolled in the same course, the instructional system for their course differed considerably from student to student. If the classroom environment is one of the contexts that facilitates interaction, then students in different sections had different opportunities for interaction. Similarly, if the instructional choices and moves made by the instructor create different systems of activity (e.g. completing a VPython assignment, watching a pre-lecture video) then students may have different starting points for engaging in their course-work.

The observational data provides insight into how students engaged during class time in instructional activities. To understand how they engaged in out-of-class activities like studying in groups or using the practice problem review website, I turn to the data from the surveys and from the practice problem website to offer a bit more description about students' out-of-class behavioral engagement. This provides a context for the results I report in the following sections that address the second research question. This data prevents a portrait of temporal changes in students' behavioral engagement.

Descriptive findings from survey and learning analytics data

In this section, I report the descriptive results of changes to the three primary dependent variables: collaborative behavior, use of a practice problem website, and course grades. First, I describe the evolution of the course network over time. Second, I provide an overview of how students' use of the practice problem website changes over time. Finally, I report how students' grade changed between the first exam and the end of the course. These results further illustrate the need to conceptualize course-work engagement as an ongoing dynamic process.

Network Change. The number of connections present in the network decreased substantially between the two exam periods (see table 13 Network Census). Out of all potential connections among students, only 0.01% are present in the period before the first exam (n=338; table 13). Social networks, as opposed to inorganic or animal networks, are traditionally sparse, so a low-density finding is not surprising (Robbins, 2015). Density, in the context of a human social network, indicates the amount of connectivity in the network. Density refers to the percentage of observed connections out of all total possible connections in the network. Sparse networks, like the one I observe in this study, make collaboration and resource sharing difficult. Individuals tend to stay within their small cliques in sparse networks, and individuals seeking to form new relationships can find this challenging. The density indicates the tendency within the network for individuals to

form collaborations and the change in density between the two time-periods indicates the tendency within the network to sever, maintain, or increase collaborations. In this network, students' tendencies to collaborate decreased over time.

Table 13. Network Census

	Before Exam 1	Before Exam 3
Connections	338	228
Density	0.01%	0.007%
Mutual Connections	28%	37%
Transitive Triplets Census	16	17
Mutual Dyads Census	48	42
Unreciprocated Dyads	242	138

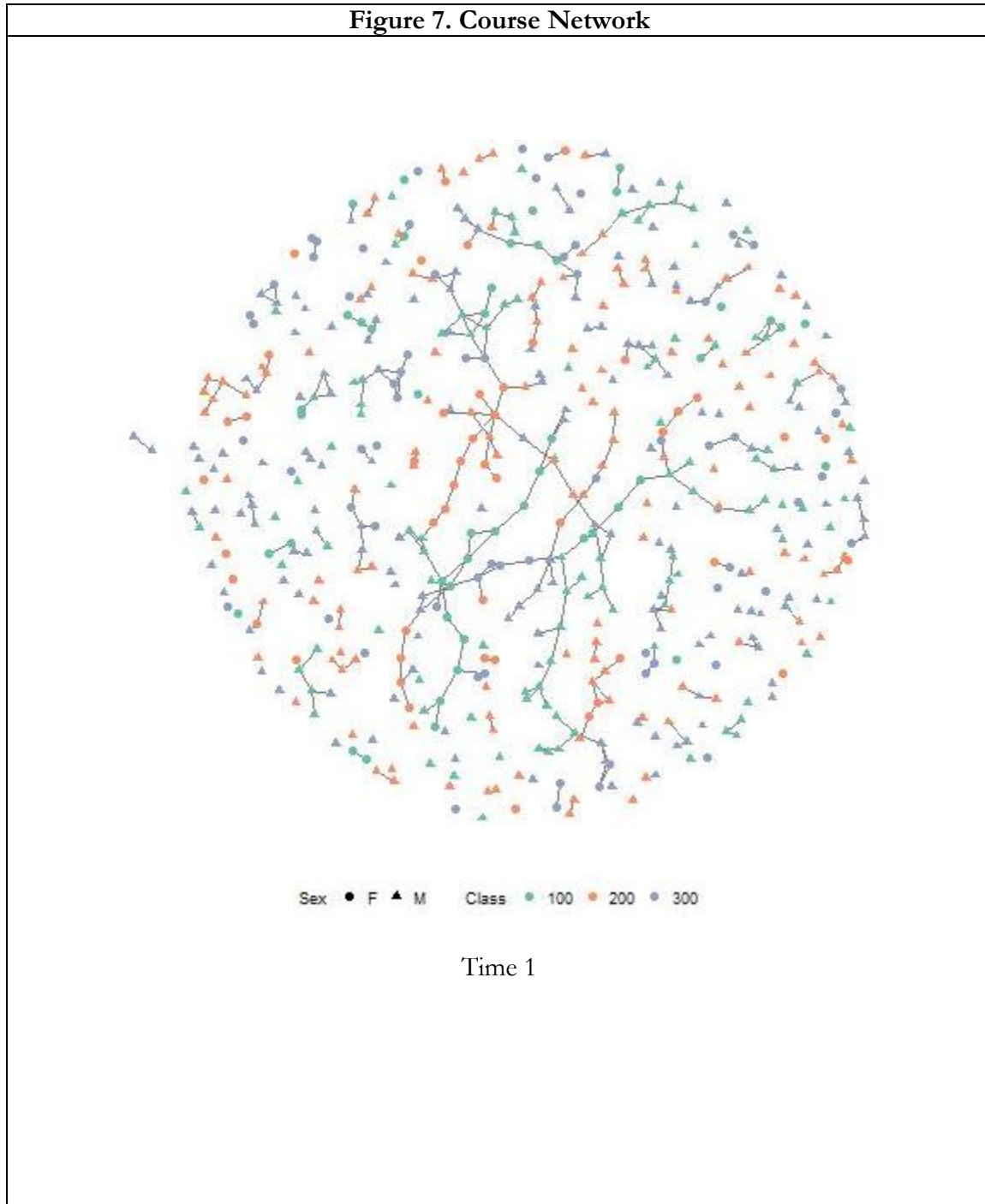
The tendency to participate by lecture section was relatively consistent with the trend observed in the course network. For example, in-class A the density of the network for that lecture section decreased from 0.3% to 0.1% between exam 1 and 3 (that is, the period between survey 1 and 2). In-class B, the density decreased from 0.2% to 0.1%. The density of the classroom network in-class C also decreased by about 0.017% between exam 1 and 3.

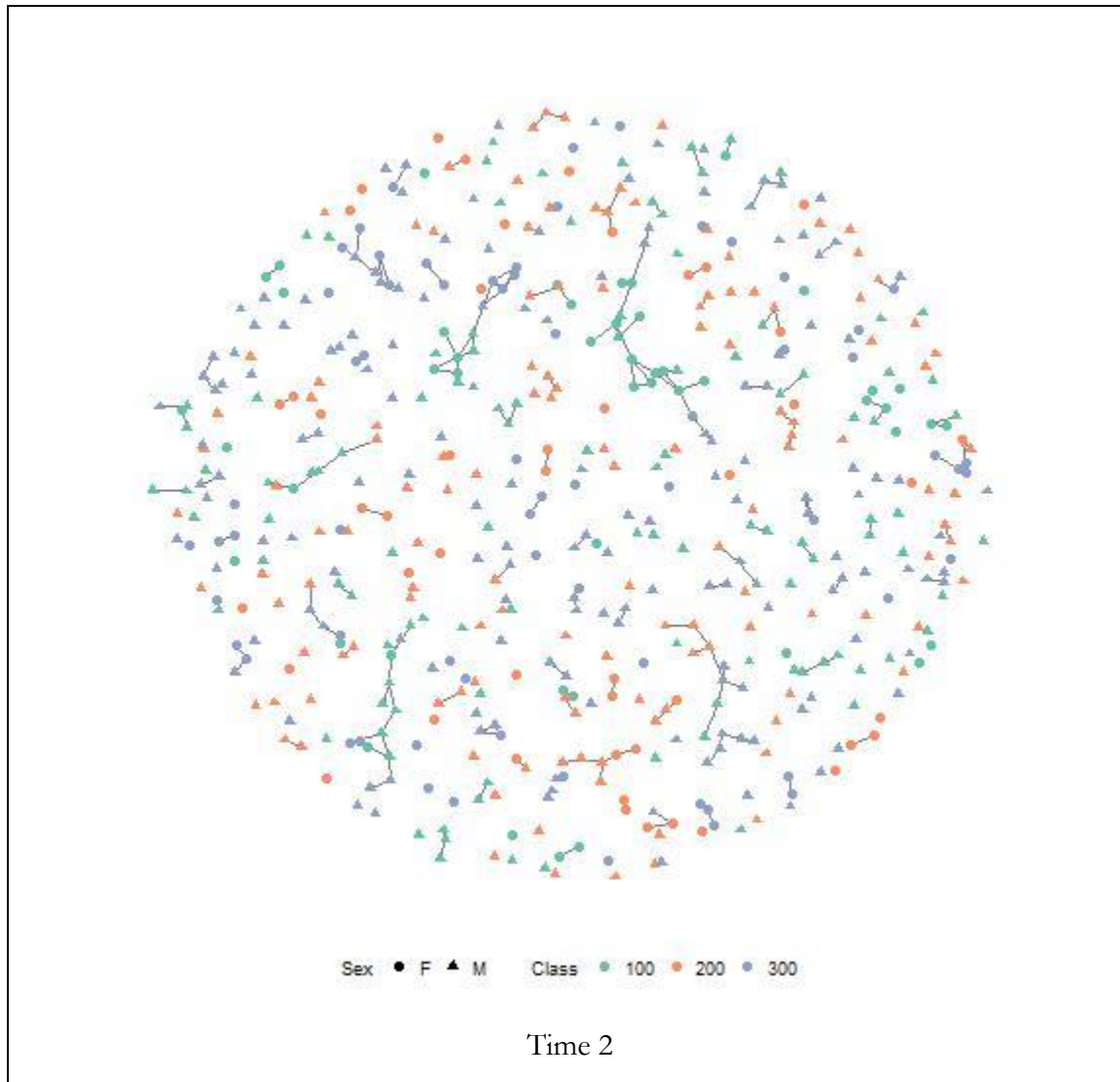
Before the course began, students reported pre-existing relationships that crossed lecture sections. For this reason, I bounded the network to include any student who was enrolled in one of the three lecture sections. My original intention was to bound the networks to each course section, as I assumed students would work only with other students in their lecture section. However, during observations and through conversations with students in the three sections it became clear that students' collaborative ties ran across the three lectures.

Including all students enrolled in the course in the network allowed students to report collaborative study relationships they had with students in other lecture sections. These relationships were common before the first exam, but they were unlikely to persist through the second survey administration. Analyses show that students reported collaborating with, at most, five other students at any point in the semester, but most students reported no collaborators. In figure 7 (below), the

large connected component on the left hand of the graph includes students from all three lecture sections. This connected component breaks up in the period before the third exam (i.e., the second survey administration), when most students are connected through smaller cliques of peers in the same lecture section.

Figure 7. Course Network





Between the two-time periods, the network contracts substantially (from $n=338$ connections to 228 connections). Within the network, many of the disappearing connections appear to be from relationships where one student nominates a peer (who in turn does not reciprocate the nomination; from $n=242$ to 138). Unreciprocated relationships were unlikely to be maintained between the two data collection periods, decreasing by 42%. Reciprocated relationships also decreased by about 35%. Of the 90 mutual relationships reported at time 1, only 58 were present at time 2 (see table 14, Dyad Census). In general, the number of collaborative relationships in the course network shrunk substantially.

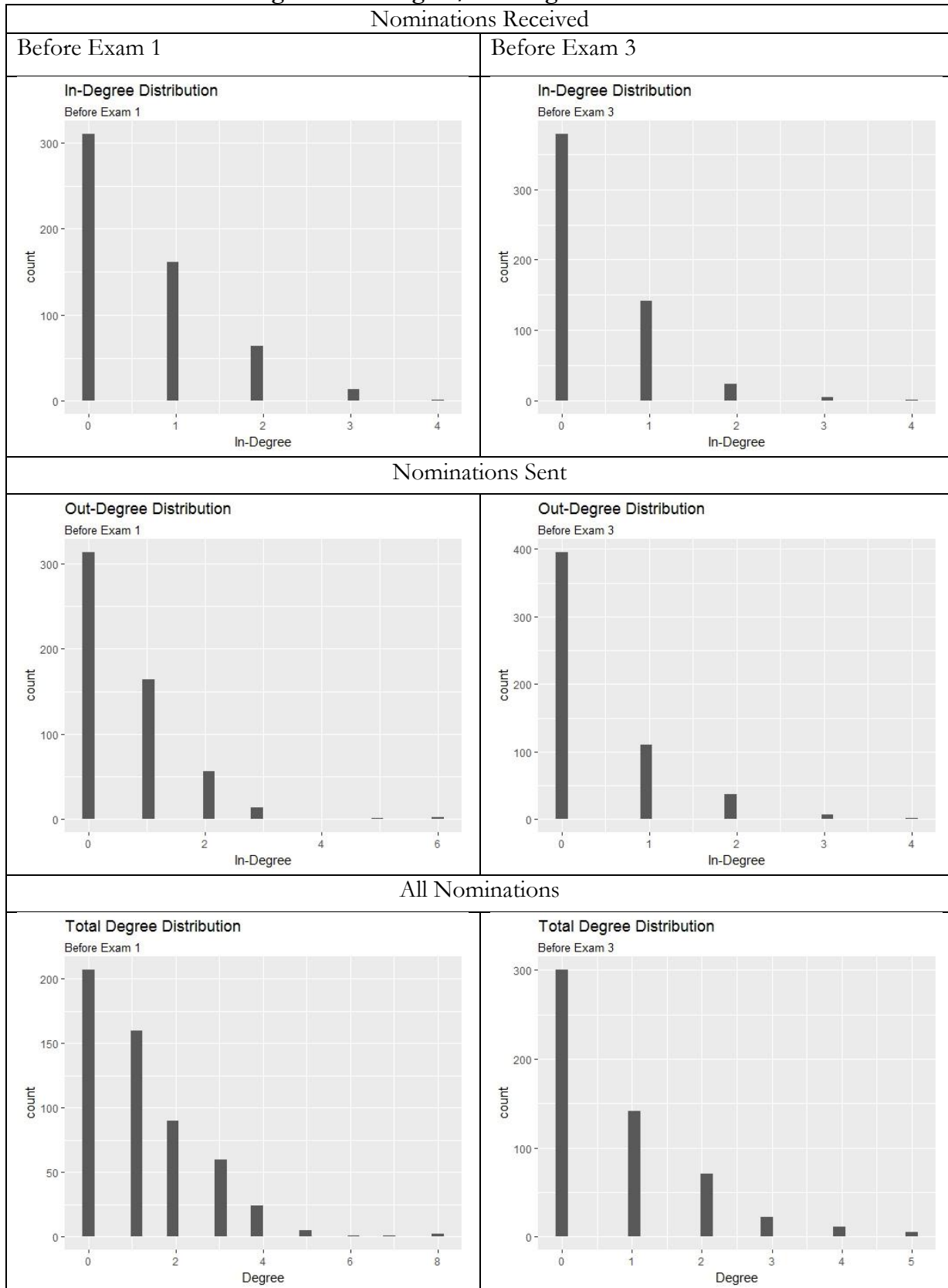
Table 14. Dyad Census

Before	Mutual	Unreciprocated
First Exam	90	242
Third Exams	58	138

Over time, there are fewer students reporting 1, 2, and 3+ collaborators, and fewer students are receiving 1, 2, and 3+ collaborations (see figure 8). This is most apparent among the total degree distribution, where the number of students who neither nominate or are nominated increases from 207 to 300.

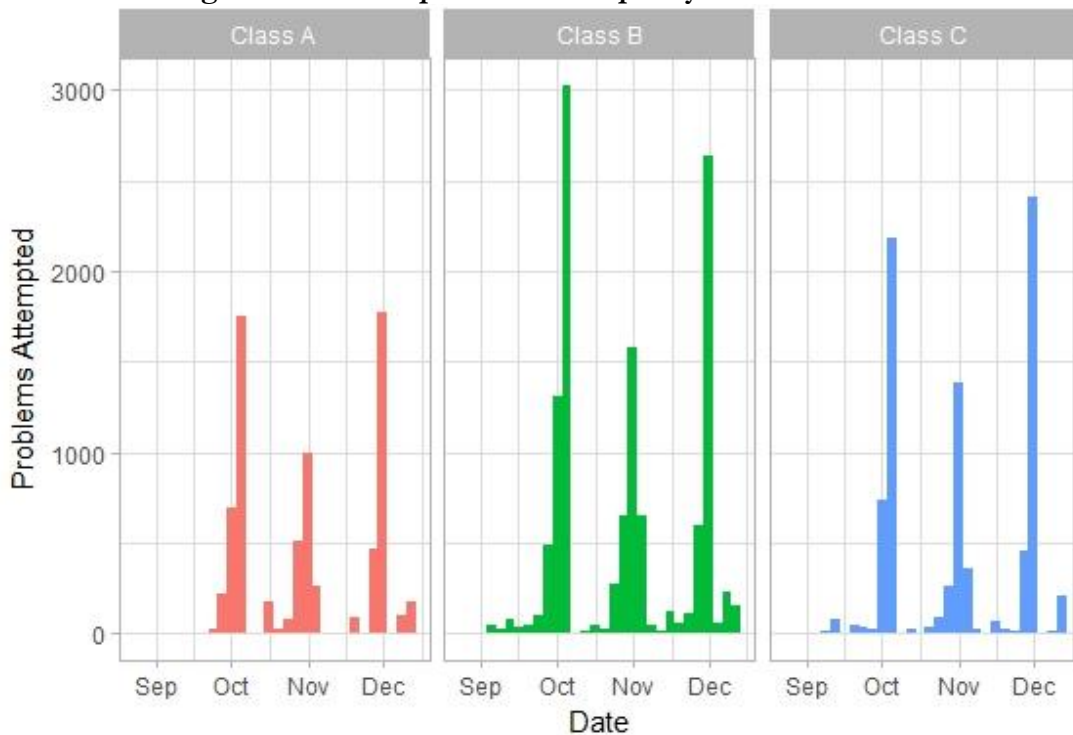
Although students were making changes to their course networks over time, there is no broad mechanism that explains how and when students sorted into new collaborations. In general, however, students were simply not collaborating with their peers in the way that I expected to observe in this study. I expected, given the interactive nature of the instructional approaches used in-class A and B that students would continue those interactions outside of the classroom. The students who did engage in study collaboration outside of class, mostly decreased their reported collaborations from the period before the first exam to the period before the third exam. Students may be testing out potential study partners, revising their strategies over time based on feedback. A slight majority of students were similarly seemed disengaged from the Practice Problem Application tool, the use of which I describe in the next section.

Figure 8. In-degree/Out-degree Distribution



Students' Use of the Practice Problem Application. In this section, I provide a descriptive overview of students' use of the practice problem website tool. The practice problem tool provided students with a random multiple-choice question drawn from a prior exam in the course. As shown in figure 9 (below), students' use of practice problems increased substantially in the lead up to each exam. There are some variations in adoption. For example, on average, students' in-classes B and C started using the application to review material earlier than students in-class A.

Figure 9. Practice problem attempts by lecture section.



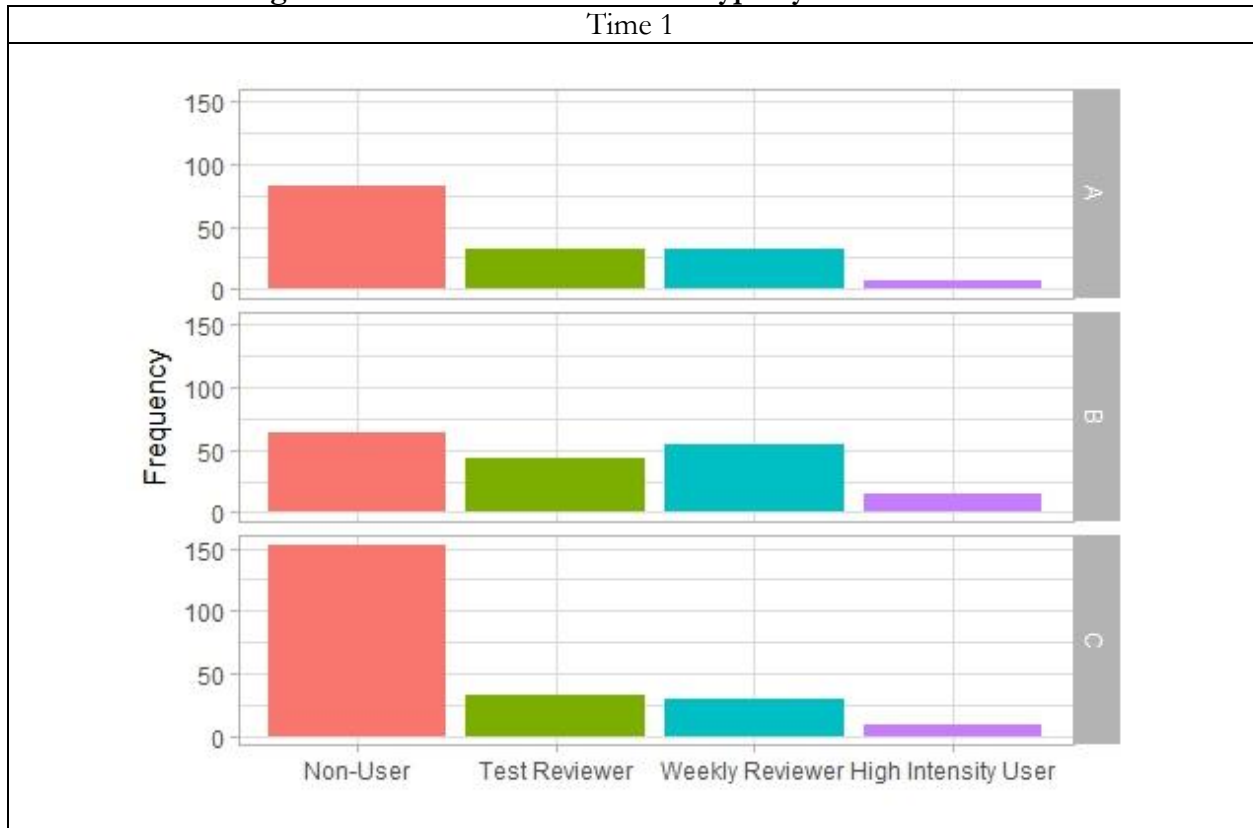
As I described in Chapter 3, in both time-periods students received a classification based on their intensity of use of the practice problem website (either Non-Users, Test Reviewers, Weekly Reviewers, or High-Intensity users; see table 15 below). Similar to peer collaboration, students in the course were unlikely to adopt the practice problem review application as part of their study strategies. Between the two time-periods, 67 students across the three courses decreased their use of the practice problem application, 104 increased their use, and 379 had constants use patterns.

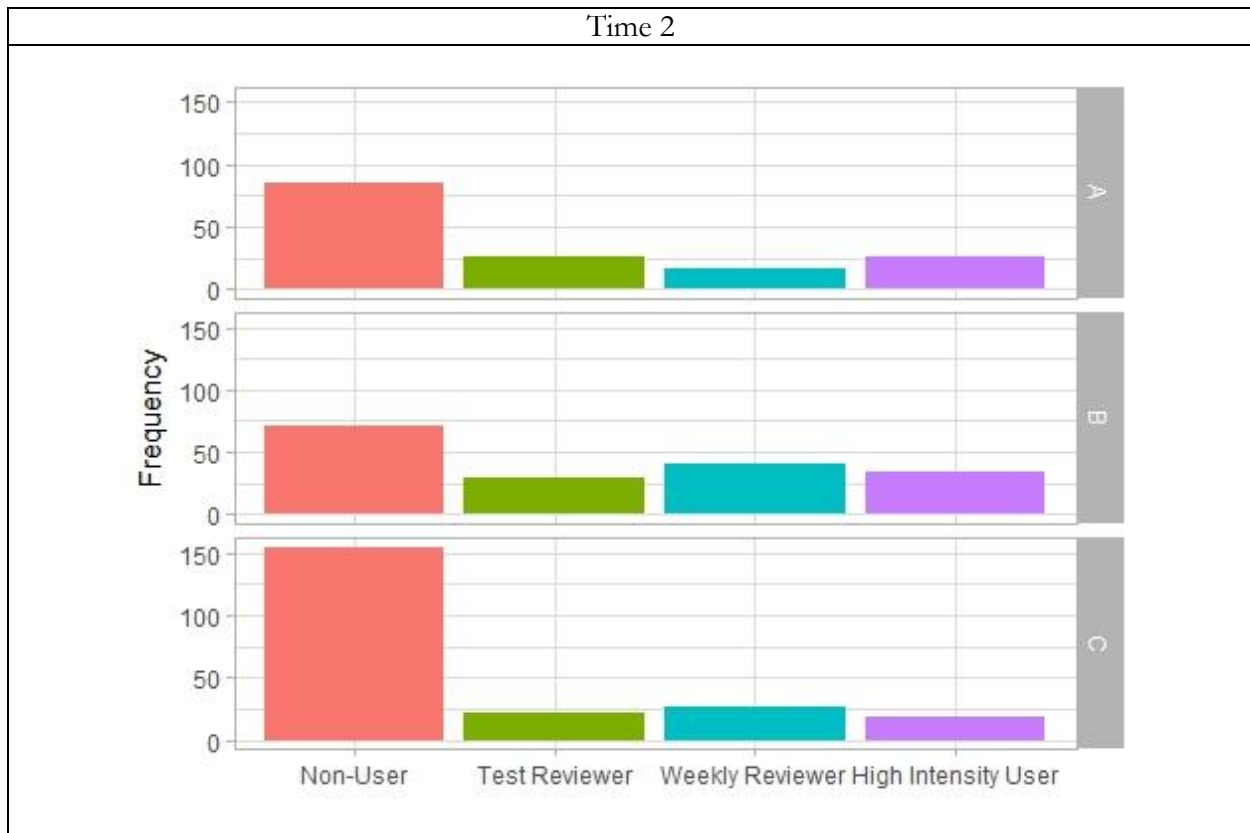
Table 15. Practice Problem Classification across time periods.

Practice Problem Use Type	Time-Period	
	Before Exam 1	Before Exam 3
Non-Users	298	310
Test Reviewers	107	78
Weekly Reviewers	116	83
High-Intensity Users	29	79

The distribution of users in each class among classifications over time can be seen below (figure 10)

Figure 10. Practice Problem User Type by lecture section.





Across the three classes, the number of Non-Users and High-Intensity users increased over time, while the numbers of students who could be classified as Test Reviewers and Weekly Reviewers shrank. The number of Non-Users increased from 298 to 310 between Time 1 and 2. Test Reviewers and Weekly Reviewers decreased (107 to 78; 116 to 83 respectively). High Intensity Users increased by 63% (29 to 79).

Table 16. Practice Problem Use classification by lecture section

	Class A		Class B		Class C	
	Exam 1	Exam 3	Exam 1	Exam 3	Exam 1	Exam 3
Non-User	83	85	63	71	152	154
Test Reviewer	32	26	43	30	32	22
Weekly Reviewer	32	16	55	41	29	26
High Intensity	6	26	15	34	8	19

Grade distribution over time. As the network decreased in size, and students made changes to their use of the practice problem application, academic performance was relatively constant. Nearly equal number of students saw their academic performance decline (n=128) and

improve (n=134) by at least a letter grade between exam 1 and exam 3. The remainder and majority (n= 288) held constant.

Synthesis of descriptive findings. It appears that, in the course, students' behaviors, on average, changed over time while their academic performance held constant. It may be that early in the semester students are testing out strategies, and over time they refine the strategies that help them maintain their preferred level of academic performance. Students explore collaboration options and they test out the practice problem technology. These results indicate sufficient change over the course of the semester that stochastic analyses are needed to capture the role of time in students' dynamic course-work engagement.

To understand how the significant relationships among students' collaborative behavior and their use of the practice problem website may change over time (RQ2A), I estimate two analytical models in the next section that account for the potential dynamic influence of change and time on course-work engagement. First, I identify significant factors that predict behavioral engagement in collaborative learning and practice problem website use (RQ2A) holding constant students' social identities, course level factors (e.g., class enrollment), and their beliefs about community. Next, I estimate a fixed effects linear model to estimate the significance of changes in sense of community and motivation as it relates to changes in students' course grade (RQ2B). These models address the second research question I describe at the end of chapter 2.

RQ2A: Stochastic Actor Based (SABM) Results

Measuring course-work engagement at one point in the semester misses the complexity of how students form and participate in different study behaviors. In this section, I employ a time series approach to modeling that identifies significance across changing behaviors and relationships. Referred to as stochastic actor based modeling (SABM), this approach estimates how changes among different behaviors and beliefs might be significantly related in determining

future behavior and relationships. In this study, students' behaviors and beliefs can change over time. SABM permits analysis that identifies a significant relationship between changes in an affective state and a student's odds of participating in a social network, for example. The results that follow for this section are all components of one analytical model (see appendix D for results in one table), but I report them in parts to ease interpretation.

Structural Network Effects. To account for the structure of the (admittedly sparse) course network on students' participation in collaborative behavior, structural network influences are estimated. Only a few key influences are estimated because fewer than half of the students participated in the network (see table 17, below). In the observed course network the number of reported relationships decreased over time.

Table 17. Structural Network Effects

	Log Odds	Standard Error
outdegree (density)	-9.052**	(3.471)
reciprocity	5.492***	(0.820)
transitive triplets	4.593**	(1.693)
transitive reciprocated triplets	-3.720	(3.921)
3-cycles	-1.864	(3.434)
indegree - popularity (sqrt)	-1.155	(0.823)
indegree - activity (sqrt)	-0.428	(1.129)
outdegree - activity (sqrt)	-0.625	(2.494)

† p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001;

The negative density effect indicates that students are likely to be selective as they choose collaborative partners, and their odds of participating in the network decrease over time (B=-9.052***). Positive reciprocity suggests that students will be likely to reciprocate collaborations for which they are nominated (B=5.492***). A positive co-efficient for the transitive triplet effect indicates that students are likely to be friends with the friends of their friends (B=4.593**).

The remaining structural effects were not significant although they do illustrate trends in peer collaborations. The negative term for transitive reciprocated triples (-3.720) and for 3-cycle

relationships (-1.864) suggests that there is hierarchy among relationships in the network. In small groups, one student is likely to be the source of many of the relationships in the group. Among triadic groups, very few participants received many nominations. A few students in the small cliques that emerged at time 2 received most of the nominations in the group, making them the fabric that tied cliques together.

Influences on collaboration. Students who received higher numbers of collaboration nominations from peers were unlikely to add to their collaborations over time (in-degree popularity=-1.15). In contrast, students who reported more collaborators were more like to increase the collaborations they reported over time (out-degree activity=0.428). An inverse (albeit not significant) relationship exists here between popularity in the network and activity. The more popular a student is the less likely they are to add new collaborators. Students who want to collaborate, but are unpopular make more attempts to seek out partners for mutual relationships.

The lack of activity among popular students may also be a byproduct of a ceiling effect of the size of groups. Although groups larger than four existed, these groups were likely to split off into smaller cliques after the first exam. Additionally, demographic and socio-cultural factors are significantly related to who is “popular.” I describe the results related to social identities and socio-cultural factors in the next section.

Table 18. Social Identity Influences

	Log Odds	Standard Error
Receiver: Underrepresented	-1.258	(1.099)
Sender: Underrepresented	-0.006	(1.217)
Homophily: Race/Ethnicity	-0.276	(1.055)
Receiver: Men	0.221	(0.379)
Sender: Men	-1.298**	(0.479)
Homophily: Gender	0.718†	(0.416)
Receiver: International Student	-0.621†	(0.322)
Sender: International Student	4.523*	(1.891)
Receiver: Friend	-0.312	(0.375)
Sender: Friend	1.461*	(0.714)

† p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001;

A handful of social identity influences were significantly related to students' tendency to participate in the network over the course of the semester. Men in the course were less likely to nominate collaborators (Sender=-1.298**) and more likely to receive collaborations (Receiver=0.221) than women. On average, there is a significant preference in the network for gender homophily among collaborators (Same=0.718†). International students were much more likely to nominate collaborators (4.523*), and were unlikely to be nominated as collaborators (-0.621†). Students who reported they worked with friends were much more likely to nominate collaborators (1.461*) in comparison to students who did not work with friends.

Table 19. Academics and Course Level Influences

	Log Odds	Standard Error
Homophily: Undergraduate College	0.029	(0.391)
Homophily: Undergraduate Year	0.414	(0.366)
Homophily: Lecture Seat	0.115	(0.372)
Homophily: Lab Section	0.960*	(0.443)
Homophily: Lecture Section	3.633**	(1.393)
Similarity: Practice Problem Use	0.424	(0.610)
Similarity: Academic Performance	0.272	(0.881)

† p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001;

Students in the same lab section (0.960*) and the same lecture section (3.633**) had higher odds of collaborating. No other factors had a significant relationship to collaboration, including students' sense of community and similarity in their use of the practice problem application.

Table 20. Sense of Community (Affective Academic Beliefs)

	Log Odds	Standard Error
Receiver: Campus Academic Community	0.270	(0.162)
Sender: Campus Academic Community	0.088	(0.310)
Receiver: Classroom Academic Community	-0.173	(0.189)
Sender: Classroom Academic Community	-0.172	(0.257)
Receiver: Classroom Social Community	-0.126	(0.175)
Sender: Classroom Social Community	-0.235	(0.265)
Receiver: Campus Social Community	-0.137	(0.284)
Sender: Campus Social Community	-0.235	(0.265)

† p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001;

Influences on Selection. Selection tables report the odds that a sender would select a receiver based on different characteristics. These tables are calculated by determining the odds that a sender possesses one identity trait and that they would send a tie to a receiver with a similar or different identity trait. Selection tables 17 to 19 report the significant influences on students' odds of sending a tie.

Table 21. Sender-Receiver Selection Table for Gender (Odds Ratio)

	Women	Men
Women	3.026	1.124
Men	0.566	1.00

Women were more likely to report collaborations with other women (OR=3.02) when compared to men. They also had positive odds of reporting ties with men (1.12). In contrast, men were unlikely to report collaborations with women (0.56), and were only slightly more likely to report collaborations with other men (1.02). Figure 7 (above) displays the network, in which men are 1) unlikely to report collaborators and 2) most likely to be connected to other men. Women, in

contrast, are connected to students of either gender, and are more likely to serve as the bridge between students.

A similar dynamic occurs among international students, where students who are not U.S. Citizens, permanent residents, or graduated from a U.S. high school were much more likely to choose similar peers, but also had positive odds of reporting domestic students. In contrast, domestic students had negative odds of reporting an international student as their collaborator and only slightly positive odds of collaborating with like peers.

Table 22. Sender-Receiver Selection Table for Citizenship (Odds Ratio)

	International	Domestic
International	2.499	1.525
Domestic	0.412	1.036

Students who reported that they were friends with their collaborator (whether that relationship was reciprocated or not) were more likely to collaborate than students who did not report their collaborators as friends.

Table 23. Sender-Receiver Selection Table for Friends (Odds Ratio)

	Non-Friends	Friends
Friends	8.689	13.40

Changes in practice problem website use. One of the affordances of the SABM approach is that estimates can be derived for changes in individual behavior in addition to changes in the network. The SABM allows researchers to estimate multiple simultaneous (interdependent) outcomes. For example, the results above estimate significant relationships to network participation. The results I report below estimate significant relationships to practice problem use and academic performance. However, the estimates for the course network use the observed data related to practice problem use as a constraint for estimation. The network described above exists within the limits of the behaviors estimated below.

In the next section, I report the results of the changes in use of the practice problem website, controlling for the structure and observed change in the network. The negative linear term

and positive quadratic term for the use of the practice problem application suggest that students tend to increase their use of the practice problem website once they become adopters (table 24). The negative linear term estimates the probability that students' practice problem use will increase in a linear fashion between the two time-periods. The quadratic term accounts for non-linearities in changes to students' practice problem website use. No other factors were significantly related to the use of the practice problem website, including socio-demographics, the nature of website use by peers, and students' reported levels of technological proficiency.

Table 24. Practice Problem Website behavioral change.

	Parameter	Standard Error
linear shape	-0.907***	(0.158)
quadratic shape	0.666***	(0.066)
isolate (no collaborators reported)	-0.004	(0.212)
average use of problem application by peers	0.050	(0.234)
Effect from technical proficiency factor	-0.069	(0.199)
Effect for Black, Latinx, Native American & Native Hawaiian students	0.294	0.237
Effect for Women	-0.117	(0.175)

† p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001;

Synthesis of SABM findings. Network, course, and individual level influences all were significantly related to students' odds of reporting collaborations over time. The configuration of relationships may influence students' tendency to maintain their collaborations or to participate in new collaborations. Students who were in mutual relationships were more likely to maintain and were less likely to seek out new partners. Students who shared space and time (lab and lecture sections) were also more likely to collaborate. In general, students were selective about who they worked with (if anyone at all), and this extended to social identities. Women and international students appear to have found themselves on the margins of collaborations more often.

The results in table 14 indicate the important role of social identities and cultural context on students' course-work engagement. Students' social roles have a potential impact on their access to

different opportunities in the classroom. Similarly, students' ability to integrate into the network informs their ability to persist in the network.

These results also suggest a potential unintended consequence of collaboration. If students' collaborations are influenced by the classroom environment then their study strategies might also be influenced by their social interactions in and out of the classroom. This is apparent from the network participation model, which indicates that students are significantly less likely to choose partners that do not resemble them if they are in the majority (e.g., white, male). Are students' use of the practice problem website, then, also susceptible to social influence?

Peer Influence and Practice Problem Use. To address the question of social influence in practice problem website use, I estimate the odds of peer influence to account for the multiple ways that practice problem use is represented in the model. For practice problem application use, the linear, quadratic and average receiver terms are included in a simple additive evaluation function. Influence tables are calculated by estimating an evaluation function for a behavioral outcome (as opposed to a network outcome).

Table 25. Sender-Receiver Influence for Problem Roulette Use (Odds Ratio)

	Non-User	Test Reviewer	Weekly Reviewer	High Intensity
Non-User	1.579	3.013	5.748	10.97
Test Reviewer	0.634	1.241	2.368	4.517
Weekly Reviewer	0.254	0.498	0.975	1.861
High Intensity	0.102	0.20	0.391	0.766

Influence tables estimate the probability that a sender takes on the characteristics of a receiver over time. Table 25 shows that, for example, non-users who collaborate with non-users are likely to maintain their method of non-use. Non-users at time 1 are 3.01 times more likely to increase their practice problem website use if they work with Test Reviewers. As non-users collaborate with peers with increasing intensities of practice problem use (that is, students who use the practice problem website only before tests, those who use it on a weekly basis, or those who are

high-intensity users), non-users tend to increase their use of the website. This increase in practice problem use is evident for Non-Users, Test Reviewers, and Weekly Reviewers—a user who collaborates with individuals who use the application more than they do, is more likely to increase their practice problem use in a way that resembles their peers' use as the final exam approaches.

RQ2B: Fixed Linear Effects Model for Course Grade

Across the three sections, many students never participated in collaborative study behavior or used the practice problem application. Students who participated in study groups and/or used the practice problem website revised their strategies for peer collaboration and study technology use as the course progressed. The students who did use these resources were likely to adjust the frequency and intensity of this form of engagement as the course progressed. For example, students reported far more collaborative partners before the first exam than they did before the third exam. Similarly, for students who adopted the practice problem application, twice as many students increased their use over time as decreased their use. Engagement is a dynamic process driven by students' agency to direct their time, energy, and interest into study strategies. To determine how this dynamic process informs academic performance, I next estimated changes in motivation and sense of community alongside changes in the two forms of behavioral engagement.

The fixed effects model explores the relationship among changes in collaborative study behavior, practice problem website use, cognitive and affective academic beliefs, and changes in a student's grade in the course between the first exam and the end of the term. A one unit increase in the practice problem intensity scale would be predict a change measured in grade points (out of 100). This additional analysis is needed because, as I noted in chapter 3, the SABM analysis only accounts for initial values of beliefs when estimating outcomes. To address the framework I outlined in chapter 3, I operationalize the changing relationships I believed to be significant among course

beliefs, affective beliefs about academic community, and behavioral engagement with out-of-class study groups and the practice problem website.

Identifying if there is a significant relationship between changes in motivation and changes in grade performance, for example, could contribute to theorizing about how course-work engagement develops over time. The fixed linear model approach holds constant all factors that do not have the potential to change over time. Prior research suggests that course performance differs between men and women in introductory physics lecture courses (e.g. Koester, Gromm, & McKay, 2017). To observe if differences by gender emerge over time, I included an interaction term for time and gender in the final model.

Table 26. Significant Influences on changes in course grade between the first and final exam

	Coefficient	Standard Error
Practice Problem Website Use Scale	0.668	0.592
<i>Affective Academic Beliefs (Sense of Community Factor Scales)</i>		
Campus Academic Sense of Community	-0.056	0.496
Classroom Academic Sense of Community	0.286	0.372
Campus Social Sense of Community	0.178	0.444
Classroom Social Sense of Community	0.062	0.384
<i>Course Beliefs (Expectancy Value Factor Scales)</i>		
Attainment Value	-0.632 *	0.597
Competency Beliefs	0.333	0.359
Perceived Cost	0.557	0.515
Intrinsic Value	1.211 *	0.519
Utility Value	-0.886	0.493
<i>Network Participation</i>		
Changing In-Degree	0.127	0.551
Changing Out-Degree	-1.633 **	0.530
<i>Demographics</i>		
Effect for Women (Women x Time interaction)	-2.034 **	0.922
Effect for time	2.321 **	0.787
<i>Total Sum of Squares: 20334 Residual Sum of Squares: 18606</i>		
	R ² : 0.085	Adj. R ² : -0.888
F-statistic: 3.00 on 14 and 453 DF, p-value: 0.0002		

† p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001;

A few factors were significantly related to changes in students' course grade during the semester. Two course beliefs are related to changes in academic performance. A one unit increase in

students' intrinsic interest in the study of physics (intrinsic value factor) was associated with a 1.210-point increase in a student's course grades after the first exam and the end of the course ($p < .05$). It is perhaps intuitive that students who find that they enjoy the course and are engaged by the subject matter would do slightly better over time. In contrast, student who reported an increased belief that the course was important for their future goals (that is, their utility value for the course increased) experienced, on average, a 0.632 point ($p < 0.1$) decrease in their course grade over the semester.

Contextual factors like students' network participation and the effect of gender across time were also significantly related to final academic performance. On average, all students' performance over time increased by 2.32 percentage points ($p < .01$), but women's performance decreased by 2.03 percentage points ($p < .10$). At the end of the course, women left with a grade penalty when compared with their male peers. Women's grades decreased between the two survey administrations, and they left the course with lower final grades on average. This course has, historically, had a significant performance difference between the average performance of men and women, controlling for ability (Koester, Gromm, & McKay, 2017). It is worth noting that the time interaction here is significant. It may be that after women students receive their first grade they respond in different ways than their male counterparts.

For each collaborator that a student added after the first survey administration, their average performance decreased by 1.62 points ($p < .05$) between the two time-periods. Students were unlikely to add new collaborators in the network over time, so this finding suggests that students who were network outliers—who are working against the general preferences of the network—may be underperforming in the class over time. This group was so small that further research is needed to verify this result in other contexts, especially contexts where network change was more prevalent.

The results of the observations, stochastic actor based model, and the fixed linear model suggest revisions to the conceptual framework for course-work engagement I proposed at the end

of chapter 2. Specifically, many of the significant relationships I expected to observe (e.g. increased sense of community and increased study group participation, increased practice problem website use and improved grade) were not present. Instead, the importance of social identity for network formation became clear, as did the importance of potentially settling upon a study strategy early in the course. In the next chapter, I revise the conceptual framework for engagement in large lecture courses with these findings in mind.

Chapter 5: Course-work Engagement in Large Science Lecture Courses

Large science lecture courses limit the potential for student/instructor interaction, reducing the sort of personalized instruction that may be easier to facilitate in intimate classrooms. Instead, large lecture courses have historically relied on an industrialized model of information delivery. Despite substantial interest in instructional interventions to increase personalization, we know little about how students develop strategies for completing their course-work in this large lecture context. To improve the design and implementation of instructional interventions, especially those that involve technology, a more nuanced understanding of how students respond to instruction in large lecture courses is needed.

The aim of this study was to outline a conceptual framework describing how undergraduates engage in their course-work in large lecture courses. We can think of course-work engagement as the set of practices that are part of students' efforts to successfully complete a course. Course-work engagement is thus goal-oriented behavior, shaped by the beliefs that individual holds about his- or herself and the course. Based on a review of the literature, I identified three primary influences on course-work engagement: beliefs about the course and experiences related to those course beliefs (e.g. Eccles, 2015), sentiments about the course community (e.g. Rovai, 2002), and behavioral practices that are part of a students' participation in the work of the course (e.g. Harper & Quayle, 2014).

For this study, course beliefs refer to a students' expectations for success in the course, their intrinsic interest in the course subject and course-work, the value they place on being successful in the course, the relevance of the course-work to their future goals and the costs they perceive in

other aspects of their lives as it relates to course participation. Affective academic beliefs refer to sentiments about the course and campus community that can influence a student's willingness to interact with others around course-work (e.g. instructors, other students, learning assistants).

I conceptualize behavioral engagement in course-work as consisting of a student's interactions with two types of study resources: out-of-class study groups (composed of peers who are also enrolled in the course) and a practice problem website. In this study, I argued that a student's willingness to engage with peers around course-work is also shaped by their sense of connection to the community in the classroom and on campus.

Since course-work engagement naturally forms within the context of a course, I also deemed the instructional activity system of the course an important influence on course-work engagement. In addition to lecturing, instructors create instructional activities designed to engage students by drawing upon learning resources like textbooks, clicker response and online homework systems, and laboratory demonstration units. An instructor's academic plan is a blueprint for action (Lattuca & Stark, 2009); in this study, the academic plan lays out possible courses of action for how students might take up different study resources. For example, in this study, the three instructors teaching the different sections expected students to prepare for class in different ways and used different systems of accountability. Students' responses to these expectations also varied. Both these kinds of variations resulted in differences in behavioral engagement among students in the three lecture sections.

The conceptual framework that guided this study assumed that the primary influences listed above – students' course beliefs, their affective academic beliefs, and their out-of-class study practices – affect their academic performance. I further assumed that students' beliefs about success and community would shape social and technological behavioral engagement, which would be significantly related to academic performance. I also argued that feedback students received from

faculty, their peers, and instructional technology during the course might result in changes in students' beliefs and, in turn, their behavioral engagement as the semester progressed.

Study Design

The study I designed to explore this conceptual framework was conducted in a large undergraduate introductory physics course (n=551) composed of three lecture sections, each taught by a different instructor. Students also took a concurrent lab course taught by a graduate student. I posed the following research questions:

3. How does the instructional system shape students' engagement in peer interactions and their use of digital instructional technologies in a course?
4. What are the relationships among students' participation in out-of-class study groups, their use of the practice problem website, and their course grade?

To collect data about course-work engagement, I employed a variety of methods. First, I administered two surveys (at different time points) that included validated scales for course beliefs and affective academic beliefs (Perez et al., 2014 and Rovai et al., 2004, respectively). These surveys also contained questions about study strategies, and a name generator that collected information on the peers with whom a responding student studied. Second, I conducted observations in the three lecture sections to document and understand the instructional systems in each. Third, I extracted user data from the practice problem website designed for the course. I also collected information about student performance from the course gradebook that was part of the learning management system.

To answer my research questions, I employed several data analysis approaches. First, I coded my observation field notes for major themes and I identified similarities and differences among instructional approaches. Second, I used a statistical network modeling method called Stochastic Actor Based Modeling (SABM) to identify how out-of-class study group relationships formed and to

examine students' adoption and use of the practice problem website. This analysis employed a set of controls including demographics and measures of affective engagement. Third, I used a fixed linear effects model to estimate the significant relationships among changes in students' behavioral engagement, course beliefs, affective academic beliefs, and their course grade.

Results

Before reporting the findings directly related to my two research questions, I describe the instructional activity system of the three sections of the introductory physics course that was a setting for the study. Over the course of the semester, I observed 193 class sessions and documented substantial variations in the instructional approaches used by the three instructors. Two of the instructors used an approach called Peer Instruction (Mazur, 2009) where students watched a lecture video before coming to class and spent class time working on analytical problems. To ensure that students watched the video, one of the instructors required students to complete multiple-choice questions during their viewing. The other instructor who used lecture videos required students to complete an additional programming assignment as part of their homework. The third instructor lectured in a traditional format, and occasionally had students complete an in-class practice problem, which he would identify in advance from the course textbook. This meant students in the three classes were spending their time outside class on different tasks to prepare for class time.

Results from the SABM, however, show that students across the three sections were relatively similar in their behavioral engagement with social and technological resources. In the overall course network, about 40% of the students worked in out-of-class study groups. Students were selective about choosing partners, and mutual recognition of a relationship increased the likelihood that students would study together out of the class ($B=5.678^{**}$). Students were more likely to 1) study with their friends ($B=1.78^*$) or the friends of friends ($B=4.98^*$); 2) work with

students in the same lab or lecture section ($B=1.054^*$, 3.8^{**}); and 3) seek out partners of the same gender (0.69^*).

To assess student use of technological resources I used learning analytics data to classify students into one of four ordinal categories that described their use of the practice problem website (i.e., Non-User, Test Reviewer, Weekly Reviewer, High-Intensity User; these categories are arranged in order of increasing use). A slight majority of the students in the course (about 56%) were Non-Users. The remainder was evenly split between Test Reviewers, Weekly Reviewers, and High-Intensity Users by the end of the course. While students overall were unlikely to change their use of the practice problem website during the course, among those that did, usage was likely to increase (linear= -0.90^{***} , quadratic= 0.659^{***}).

Regarding my first research question, *“How does the instructional system shape students’ engagement in peer interactions and their use of digital instructional technologies in a course?”* I found mixed evidence of the extent to which students responded to the instructional system as part of their behavioral engagement. Although class sections that provided greater opportunity for students to interact did not result in students collaborating more often, students who were in the same lecture section were more likely to work together. Overall, the features of the course that cut across sections – such as homework assignments and exams -- seemed to have little influence on how and when students engaged social or technological study resources in the course. Instead, individual level factors – specifically students’ social identity and course goals – were more likely to significantly impact their engagement.

This is not to suggest that instructors do not influence what students do in and outside the classroom. Rather it appears that the template offered by instructors for how to be successful in this class was sufficiently broad that students engaged in a variety of ways based on their specific circumstances. A student with many friends might, naturally, be pulled into collaborative study

behavior by pre-existing relationships, and students with competing demands on their time might gravitate towards technological resources. As instructors did not exhort students in any direction, nor privilege one resource above another, students were able to chart their own approach.

Students were limited, however, by course (infra)structures. The physical organization of the classroom resulted in very little social mixing during class time. Because the instructors distributed grading points differently among the three lecture sections, students were pushed in different directions by the design of the assessment approach in their lecture section. For example, students in-class A were spending their out-of-class time on for-credit programming assignments on a weekly basis. Students in-class A adopted the practice problem website about a week later than students in the other class sections. They also tended to start their review of practice problems through the website at later times than students in the other sections, typically in the lead-up to exams. The amount of time that the course accounted for in the schedules of students in-class A might have been the same as students in-classes B and C, but students in-class A had less agency in determining how they would spend that time.

The different approaches to assessment may also explain the tendency over the semester for students to gravitate towards studying with other students in their lecture section. At the beginning of the course, students crossed lecture sections to work together, but the differing requirements and approaches to instruction seem to have pushed them towards finding collaborators with a common understanding as the course progressed.

Regarding my second research question, *“What are the relationships among students’ peer interactions, their digital technology use, and their performance on assessments in a physics lecture course?”* I found that behavioral change and evolving course beliefs, but not affective academic beliefs (e.g., sense of connection to the academic and campus communities), were related to improved course grades. I estimated a fixed effects linear model where the dependent variable was students’ average grade (out

of 100 possible points) in the period immediately following the first and final exams. I found that increases in students' perceptions of the attainment value (that is, the importance of doing well on analytical problem solving and achieving a desired grade) were significantly related to decreases in their grades between the first and final exams (a 1.003* decrease on a student's final grade). In contrast, increases in students' reports of the intrinsic value of the course were significantly related to grade improvement (1.322**). As students increased the number of peers with whom they studied outside of class, their performance appeared to decline (-0.668*). These changes are small and marginal, they may not mean differences in a grade at the end of a term.

In contrast, increasing the use of the practice problem website was not significantly related to grade change. It is worth noting that while, students' grades increased by about two points, on average, between the first and final exams in the course, the grades of women students in the course decreased, on average by 1.813* points, which conforms with prior research on introductory physics (Koester, Gromm, & McKay, 2017).

This suggests some important relationships among behavioral engagement, course beliefs, and academic performance. First, students generally decreased their network participation while maintaining their practice problem use. Additionally, changes in an individual student's intrinsic interest in the course and attainment value had significant (albeit different) relationships to changes in course grade. Students who perceived increased attainment value of the course experienced performance decreases over time, but the causal direction of this relationship is not clear. It could be that decreasing performance leads to increased perception of attainment value, or vice versa. I also found that at students who continued to revise their strategy for engaging with social resources during the course found themselves at a slight disadvantage at the end of the course. It appears that the more students cycled through resources and changed their engagement strategy, the more they appeared to experience academic difficulty. It may be that students who perform poorly early in the

course continue to do so throughout the course while they revise their strategies. Alternatively, it may be that revising one's course-work engagement strategy may lead to declines in performance, especially if students are unable to settle upon an approach.

It is clear, however, that students have multiple starting points for developing course-work engagement, and that throughout the course a host of individual level factors appear to influence how they engage throughout the semester. For example, students who reported no study peers and who were non-users of the website reported spending, on average, about 6.7 hours a week studying. Although this amount was lower than that of students who engaged with peers (9.89) and who used the problem website (11.1), students were engaged in out-of-class course tasks. Students' beliefs change over time alongside changes in their engagement with both social and technological resources. Practice problem website use appears susceptible to peer influence, while social resource selection seems to respond to social norms like identity homophily. That both forms of behavioral engagement (social and technological) respond to peer influence suggests that a conceptualization of course-work engagement in large science courses requires a deeper understanding of how students interact with their peers around academics; which is not typically a major design issue for a large course.

Implications from findings. The results of the study I outline above suggest some revisions to the conceptual framework based on a review of the literature. My study identified salient influences on course-work engagement that should be considered in addition to cognitive, affective, and behavioral engagement. Additionally, the results I described above offer some insight into how time and changing beliefs and practices inform academic performance during and at the end of a course. Below, I outline a revised and expanded conceptual framework for course-work engagement in large science lecture courses that takes these influences into account.

The conceptualization of student engagement that framed this student conceived engagement as a meta-construct with cognitive, affective, and behavioral dimensions. I operationalized some aspects of each dimension to, as Friedrichs (et al., 2004) suggested, explore “all three types of engagement [cognitive, affective & behavioral] determining whether outcomes are mediated by changes in one or more components” (p. 61). My study attempts to bridge the behavioral, psychological, and socio-cultural perspectives on student engagement in higher education by examining engagement in course-work in the social context of the large lecture course. The dynamic components in this study are students’ behavioral engagement, their course beliefs, and their affective academic beliefs. As Kahu noted, “no single project can possibly examine all facets” of the complex construct of student engagement (2013, p. 770). Accordingly, in the expanded conceptual framework I identify the influence of specific contexts, changing belief states, and behaviors that contribute to the dynamic emergence of course-work engagement in large science lecture courses. This effort also responds to Jansoz’s (2012) call for research that examines the process of engagement in relation to the outcomes of engagement.

Course-work Engagement in Large Science Lecture Courses

Instructional Activity Systems. The primary contribution of this study is to position the instructional activity system in large science course as a core influence on course-work engagement. By instructional activity system, I mean the emergent and collective set of behaviors that occur at multiple levels of social interaction and with different levels of intentionality; these include the social system of the classroom, interactions among individuals, and interactions between individuals and course resources.

The instructional activity system is guided by the instructor’s academic plan, which lays out the distribution of work among the community of people and resources associated with the course. The academic plan encompasses the purpose of the course, its content, the sequencing of content

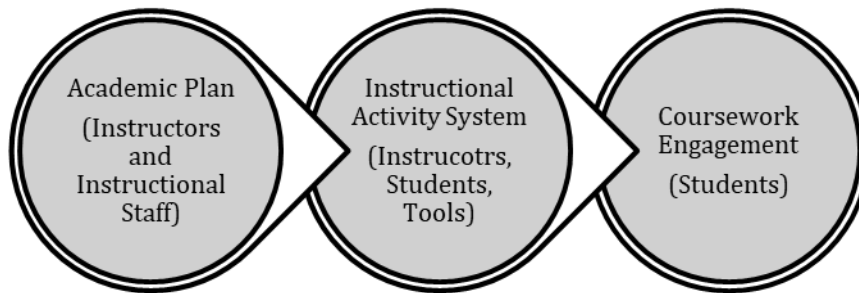
and activities, the learners enrolled in the course, the instructional processes used to engage learners, instructional resources that support instructional processes, how learning is evaluated, and adjustments made by instructors as the course progresses (Lattuca & Stark, 2009)⁴. In the case of the large science lecture course I studied, the instructors' academic plans sought to coordinate the distribution of work among the community of students and their interactions with various instructional resources used in the course. Lattuca and Stark note that the academic plan is a blueprint for course activity but likely changes as students interact with the instructor, their peers, and the instructional plan in a course. Thus, I use the concept of the instructional activity system to signify the enactment and coordination of the academic plan by the course community, which I define as the network of students that coalesces around the course. Through academic planning, instructors assign roles to artifacts like textbooks and homework assignments (in the physics course I studied, for example, these serve the roles of information delivery and assessment, respectively). This includes motivational schemes like incentivizing behavior through credit, like Instructor B providing students points for watching pre-lecture videos. Students then take up different practices (either as individuals or by coordinating amongst multiple individuals like a formal or informal study group) to complete the work of the course.

Academic planning, then, is transformed into course-work engagement through the instructional activity system, which is the functional operating system through which students perform the work of the course. Students engage in course-work. Instructors engage in academic planning, teaching, and assessment. Between the two, sits a complex system of interactions – sometimes tightly coordinated and sometimes not – among students, between student(s) and instructor, between student and instructional resource/artifact, and between instructor(s) and

⁴ It is worth noting that among disciplines there is substantial variation in how courses are taught and how students are assessed (Donald, 2002). As such, academic plans will vary substantially by discipline and field.

instructional resources/artifacts. Resources are configured to scaffold the goal-oriented work of different individuals, be they students or instructors. This act of translation from the instructor's plan to the student's plan to the student's practice is how course-work is enacted, and is depicted in figure 11.

Figure 11. Instructors' academic plans shape course-work engagement.



Classroom Environments. One of the primary sites in which the academic plan is translated into course-work is the classroom environment. The classroom environment provides a physical space for much of the performance of the instructional activity system. Theories of self-regulated learning and student engagement too often underestimate the influence of the classroom environment. Large science classrooms, for example, have specific features that encourage and discourage different kinds of engagement. Fixed seating in a large lecture hall makes small group work more challenging, both for the instructor and for students. It potentially deters the instructors from planning small group activities, and it might deter students' willingness to work in groups. In this study, the fixed seats of the large lecture hall may have made it harder to connect with peers in a less intimate space that is organized around viewing the instructor's performance. Alternatively, large lecture classrooms might offer more diversity through their larger enrollments that allow students to seek out multiple study partners.

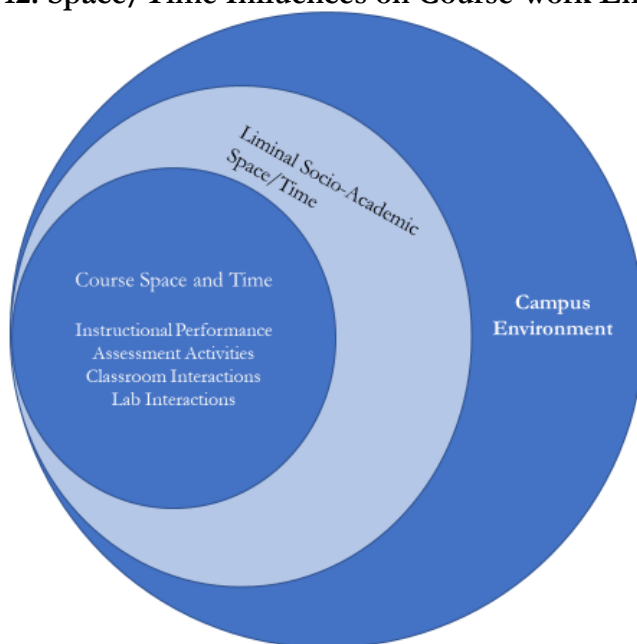
In this study, students were much more likely to report participating in out-of-class study groups with peers who were enrolled in their lecture section and their lab section. Shared space and time can shape how students select peers for socio-academic interactions, which in turn influences

socio-academic behavioral engagement in the course, which is potentially related to academic performance).

Within large lecture courses, person/instruction/environment interactions inform course-work engagement. Students who were in-classes with instructional activities that influenced how they used their time outside class—like students in-class B who received credits for watching videos before class—were pushed towards one form of interactive material engagement that potentially reduced the time available for other forms of behavioral engagement, such as reviewing the textbook or completing practice problem sets like students in-class C. Similarly, students' opportunities to participate in out-of-class study groups were shaped by norms arising from network formation. Students who had few existing relationships in the class were less likely to find study partners. Students were not excluded, *per se*, from study groups by a lack of existing relationships, but their opportunities to form relationships were limited by less accessible peers. Norms from the campus culture also appear to influence network formation, given the substantial social segregation that shape peer connections.

Students' interactions related to a course are not bounded to the time and space of that course. Instead, course-work can (and probably should) seep into other facets, spaces, and times of students' lives. There is some evidence in this study that social norms and biases present on campus inform individual students' course-work engagement (for example, the salience of social identity in relationship formation). Students' engagement in course-work, then, needs to be considered in light of how students navigate space and time on campus. Future researchers should turn their attention to the liminal space where the social world of the course meets the social world of the campus, depicted in figure 12.

Figure 12. Space/Time Influences on Course-work Engagement



The classroom environment helps to define which interpersonal interactions are part of course-work engagement and which belong to broader categories of participation and involvement in campus life. Course space and time demarcate specific types of interactions, including classroom interactions, lab interactions, and assessment activities. The performance of instruction—the embodied delivery of information by an instructor, either through lecture or demonstration—happens largely in the classroom and lab spaces. Information delivery, however, can span liminal spaces, as it did in the lecture sections in this study in which students were required to watch pre-lecture videos. That said, even traditional lecture courses use textbooks and other artifacts to mobilize student learning outside class space/time. The forms of social and technological behavior engagement that I focused on in this study belong to the transitional (or liminal) space/time of the course, where students participate in academically centered interactions in a variety of different spaces and times on campus. At other institutions, liminal space/time might account for more of student life, especially at nonresidential commuter institutions and online programs where students are often juggling work and family responsibilities.

Expansive behavioral engagement. My initial conceptual framework focused on behavioral engagement with two types of resources: social and technological. The results of this study suggest a more expansive perspective on behavioral engagement is needed. Students engaged with a variety of resources, including peers inside and outside class, study groups organized by the institution, and academic transition and mentorship programs. Additionally, students used a variety of material resources like paper practice tests, problems from the online homework system, and lecture videos to prepare for exams.

Based on my observations and the results of the quantitative analysis, I would re-characterize students' behavioral engagements as socio-academic engagements. I intend this term to include both material and socio-academic engagements (or in some cases, a mix of the two which we could call socio-material engagement). Socio-academic engagement encompasses relationships and interactions with humans involving course-work. Socio-academic behavioral engagement for the students in this course included collaborative problem solving during class time, studying with others to prepare for lecture and for exams, and working with others to complete homework and programming assignments. This kind of collaboration is common in science courses – and particularly lab courses that require that students work together to complete lab experiments. These kinds of socio-academic behavioral engagements become socio-material when they involve the use of instructional tools, such as a lab apparatus or textbook, to scaffold learning like the material aspects of an experiment.

Socio-academic engagement, in this way, not only includes, but can inform students' engagement with educational materials. We can think of this engagement with the material as existing on a spectrum of interactivity. Digital tools and technologies, such as the practice problem website used in the course I studied, have the potential to provide feedback (or at least a response); some are highly interactive (such as a digital tutor that tells students if they have answered a question

correctly and why or why not). Students also have access to non-interactive resource, such as a paper copy of a practice exams, which does not respond to users as they engage it. Students can engage with these course materials independent of other actors, but I observed no instances where students engaged with each other and did not fold educational material (e.g. paper exams, practice problem websites, calculators) into their practice. During observations, I noted that instructors referred to all course resources as productive and useful study tools. Rarely did they emphasize one approach⁵.

A new conceptual framework

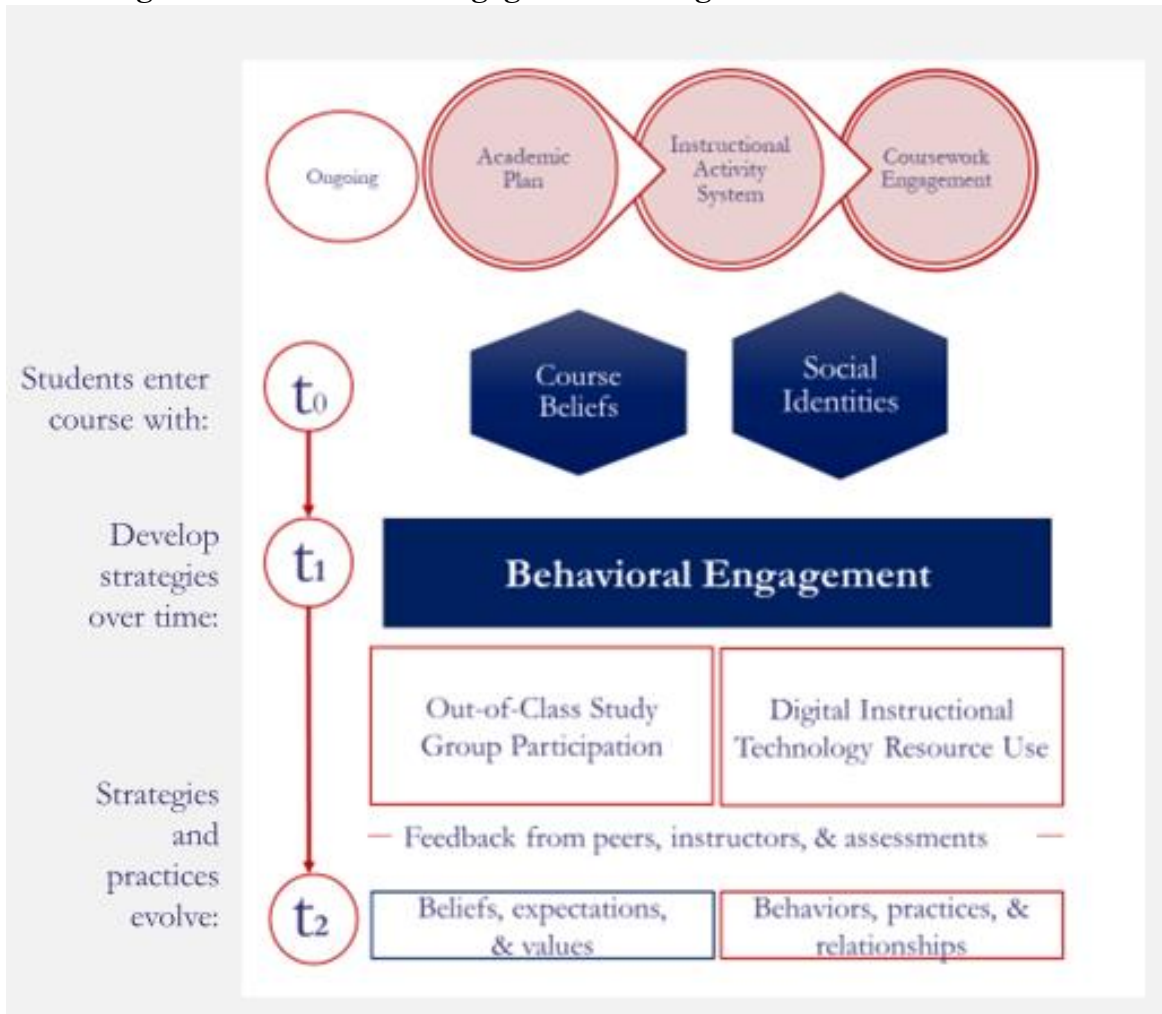
The revised conceptual framework reflects the findings of this study, pulling them together into broad categories for further investigation. The instructional activity system, as enacted by students in the classroom and in other course spaces and times, provides an interactive context for the emergence of individual course-work engagement. Students' engagement is shaped by existing and changing social relationships (which can become socio-academic interactions) as well as their existing and changing strategies for using course resources (like the practice problem website in this study). Initial and changing course beliefs, such as perceptions of the intrinsic and attainment value of the course, inform course-work engagement through their impact on performance (a notion I address in the section on outcomes below).

Beliefs systems, instructional systems, and peer relationships are the broad macro structures through which course-work engagement emerges. The micro-interactions and the individual influences that shape course-work engagement towards the needs and wants of the individual are described below. Figure 13 illustrates for scholars and practitioners the primary contexts and

⁵ The one exception was in the lead up to the registration deadline for study groups sponsored by the undergraduate college. Instructors mentioned this option a few times, and encouraged students to seek out the opportunity.

structures that are relevant to discussions of course-work engagement. In the next section, I identify specific influences and levels of analysis for future investigations and for potential intervention sites.

Figure 13. Course-work Engagement in Large Science Lecture Courses



Influences on course-work engagement. In general, course-work engagement is produced through individual and course level interactions that yield a variety of outcomes. In this way, course-work engagement is like Astin’s (1984) conceptualization of involvement as an ongoing process that occurs within an institutional context, shaped by participation in different social and academic communities. To clarify how interactions and influences come together in the specific case of course-work engagement, I identify personal and environmental influences, social and material interactions related to course-work, and the outcomes that course-work engagement yields. Course-

work engagement is a means to an end for other outcomes like academic performance, relationship development, the emergence of academic and professional identities, and (hopefully) learning. I address each set of influences, in turn, and then describe the relationship of outcomes to course-work engagement in further detail. I also identify factors that prior research indicates require further research, like how these influences might surface in campus life.

Table 27. Influences on Course-work Engagement in Large Science Lecture

Level of Analysis	Person Influences	Interactions	Environmental Influences	Outcomes
Individual	Attainment Value Intrinsic Value Social identities (e.g. gender, citizenship)	Socio-academic behavioral engagement <div style="border: 1px solid black; border-radius: 15px; padding: 5px; width: fit-content; margin: 0 auto;">Course Network</div>		Socio-academic Relationships Academic Performance
Course		[Interactive] Resource Engagement	Course Time Course Space Instructional Activities Assessment Activities	

Person Influences. Person-level influences encompass social identities and belief states. Social identities include socio-demographics like race and gender as well as academic identities like a students’ major program. Beliefs states include affective beliefs (such as a sense of being a valued member of the classroom community) as well as cognitive beliefs and processes (such as expectations for success and self-efficacy beliefs). In terms of course-work engagement, this study suggested that affective beliefs such as students’ perceptions of the attainment and intrinsic value of the course play a significant role. In this section, I posit the relationship of different social identities and course beliefs for aspects of course-work engagement.

Individual students begin a course with a set of identities that inform their course-work engagement. In this study of a large physics course in a research university, gender and citizenship were both significant predictors of out-of-class study group participation. Students who were

underrepresented in the class by gender and citizenship were more likely to attempt to participate in study groups and less to be acknowledged as study peers by students who were part of the numerical majority (i.e., men, white or Asian students, students who attended high school in the US). Social identities in the classroom are subject to the same systems of marginalization and oppression that permeate post-secondary institutions and American cultural life. Homophily – or potentially, sexism, racism, and xenophobia – may manifest through the peer selection process.

Students also enter a course with a set of beliefs about their abilities and about course-work. In my study, two forms of changing beliefs about the course were related to changes in course grades by the end of the semester. If a student entered the course with low levels of intrinsic interest in physics but developed enthusiasm for the course, her grade improved over the course of the semester. It may be that as students learn more about their intended major or develop firmer academic futures, their anxiety about performing in a course increases. We need research that identifies the relationships among students' intrinsic and attainment beliefs about the course, about their competency relevant to the course, and different forms of behavioral engagement.

I observed very little evidence that the kinds of affective academic beliefs that I studied (e.g. feeling connected to peers in the course or on campus) played a role in out of class study group participation or in student outcomes at the end of the course. There are several other forms of affect that can affect academic performances, for example, boredom (Mann & Robinson, 2009) and anxiety (Spielberger, Anton, & Bedell, 2015). Scholars should examine the relationships between these factors and course-work engagement in large science lecture courses.

Research on cognition and affect is challenging because these concepts are difficult to operationalize. Scholars have taken up the challenge of developing novel and innovative ways to collect student data about these processes, like the use of cameras and micro expressions for

capturing affective learning analytics data (see Papamitsou & Economides, 2014 for a review). In future research, I hope to explore both course and affective academic beliefs further.

Environmental Influences. Environmental influences encompass macro-structures and properties that are part of the course (and therefore external to the student). These include classroom, course, and campus spaces as well as classroom and course time. Environmental influences also include course structures that shape the instructional activity system like lectures, instructional activities, and assessment activities. In the physics course I studied, assessment activities, for example, encouraged students to engage in study behaviors that closely resembled assessments (such as practice exams). I also include the structure of the relationships among students in the course network as an environmental influence. Other scholars have identified environmental factors as important influences in college student development and learning (see chapter 3 in Patton, Renn, Guido & Quaye, 2016). These factors, I argue, can shape individual students' course-work engagement as well.

The physical space of the lecture hall becomes 'the classroom' at scheduled times. In the case of this study, at an appointed time, four days each week, students were invited to enter the lecture hall and interact with classmates, receive information from the instructor about the course, and participate in instructional activities. Instructors in the course I studied organized this time in different ways. Class A and B afforded multiple opportunities for students to interact while working on in-class problems but these opportunities were constrained by the physical environment of the lecture hall. Seats in the classroom were fixed to the floor and organized in rows, and students rarely stood up or moved to work with other students. The physical environment thus pulled the social community of the classroom into formation. Students in any of the class sections were unlikely to leave this formation at least for the duration of the class period.

One of the few times where students assemble as a class is in the lecture hall. During class time, which is bounded within-class space, students participate in the work of the course as a group. Lectures are one of the few opportunities where students have little choice about the ways in which they can participate. They can certainly choose their level of engagement—I saw many students in the back half of the classroom visiting unrelated websites during class time—but the instructional activities in which students engage are delivered to students as a group. Information is delivered synchronously, and students' decisions to not attend – either to the information shared during class or to not attend the class itself – disengages them from a core function of course-work. If there is one relative constant across the multiple forms of course-work engagement that students in which students are invited to participate, it is activities that occur in the classroom space and during class time.

Many students' network connections were shaped by their participation in exogenous groups. For example, some students noted on the survey that they studied with students in other lecture sections because they were all members of the campus marching band. Student connections (and therefore their out-of-class study groups) were fostered through participation in these groups or other shared spaces like residence halls or co-enrollment in other courses. First-year engineering majors take many of the same courses, resulting in-classrooms with substantial enrollment overlap. Further research is needed to understand how moving among multiple campus spaces and places informs course-work engagement; especially the liminal course-work spaces where students social and academic worlds intersect.

Interactions. In a variety of environments, students engage in purposeful interactions with several resources as part of their course-work. These interactions are generally along two dimensions: social or material. Socio-academic behavioral interactions refer to behavioral engagement with other human agents (students, instructors, tutors) around the work of the course. I

refer to this as socio-academic interaction to place emphasis on the focus of the interaction. Socio-academic interactions can occur in or out of the classroom. In-classroom academic interactions include working with peers on analytical problems or completing a lab assignment. Interactions outside the classroom can include reviewing material to prepare for an exam or helping a peer with a homework problem. Socio-academic interactions also include interactions with individuals who are not members of the course, like academic advisors or older students. These individuals might provide advice that helps a student develop her approach to course-work or they may provide instrumental assistance with completing homework or preparing for exams. Out-of-class social groups like living-learning communities, students' clubs and organizations, and Greek life organizations can also foster socio-academic interactions as students engage in help seeking among friends and acquaintances. It is unclear from this study what role other kinds of interactions – for example, harmful social interactions like stereotyping and microaggressions -- play in course-work engagement. Related research suggests that experiencing microaggressions in the classroom for students who are underrepresented by race or gender can negatively influence students' participation in course activities and can discourage students from developing diverse social networks (e.g. McCabe, 2016).

The students enrolled in a course are pulled into a network through their socio-academic interactions. Their interactions may become relationships, and when these relationships are mutually recognized they are likely to be durable throughout the semester. My study suggests that the resulting network of relationships structures how students access socio-academic resources. Students who are connected to many other students through mutually recognized relationships will likely have an easier time finding study partners and engaging peers around course related concerns. Students who are independent of the network or are connected to fewer partners (or connected in relationships that are not mutually recognized) may have fewer and possibly less productive socio-

academic interactions perhaps because of their lack of social connections to peers in a course. An interdependency emerges between students' agency to direct their course-work and the course social structures that limit their agency.

Student agency results in dynamic socio-academic interactions (and socio-academic relationship formation) within the boundaries created by the network, the instructional activities, and larger campus environment. For example, it is difficult for students to find and work together in heterogeneous pairs or groups by gender and race/ethnicity because physics and engineering are fields with historically low enrollments of women and minoritized students. Institutional programs such as the Women in Science and Engineering living/learning communities or the University's science and engineering bridge programs create exogenous networks of social (and academic) support in which individuals may already be engaged. These pre-existing relationships appear to increase the likelihood that students will work together, much in the same way as shared class space and time.

Material interactions encompasses the non-human resources that students access as part of their behavioral engagement. Material interactions exists on a spectrum of interactivity. Material interaction can encompass low-interactivity resources like students' use paper practice exams and hard copies of textbooks that do not respond to users. Material interaction can also include higher interactivity resources that provide feedback to students. This includes digital instructional tools (DITs). It is worth noting that while these tools have the future potential to provide formative feedback, in this study the practice problem website and the i-clicker tools used for in-class polling provided summative information about student performance.

Students' behavioral engagement in their course-work is composed of social and material interactions. In my study, many students engaged with both interactive and non-interactive materials and incorporated instructional materials and tools into their socio-academic interactions. A student

might, for example, use the practice problem website with a peer group during a study review. He might also use i-clickers during classroom discussions about practice problems. Socio-academic material engagement can pull together different resources as students configure their engagements with peers and with instructional technologies in a course.

Course network. Socio-material behavioral engagement appears to be an iterative strategy that changes relative to assessment feedback and students' increased understanding of their responsibilities and preferences. As the semester progresses, students have more information about their performance, and the extent to which their approach to the course aligns with their goals for the course.

Students' approaches to the course change over time, and this influences the network structure. In this study, the contraction of the course network was the result of students' revised study strategies. The network transitioned from a few loosely connected large groups early in the semester to fewer, and smaller, cliques of two to four students later in the term. If we operate from the assumption that the network reflects the preferences of the students (which is a basic assumption of Stochastic Actor Based modeling), we might assume that the student-actors in the network:

1. are exploring multiple strategies for preparing for class;
2. that they refine these strategies over time;
3. and that this results in a smaller network with fewer reported relationships in the course.

Students who work with peers in the network are susceptible to peer influence in a way that students who work independently are not.

As a result, socio-material behavioral engagement can diffuse through socio-academic material interactions. For example, when students participated in out-of-class study groups with peers who used the practice problem website more extensively than they did, they tended to adopt the habits of more intensive users who they connected with through studying. Socio-academic

interactions and material interactions may have a direct bearing on each other, where students in socio-academic interactions are exposed to different material interaction strategies.

Similarly, the affordances and design of instructional technologies might facilitate or deter their use in study groups. For example, in this study many lower level users of the practice problem website in this study were susceptible to peer influence but the lack of a collaborative mode for the website may have deterred even more students from working together on these practice problems. Instructional resources, including interactive resources, can thus promote or deter socio-material behavioral engagement through their affordances. Designers should keep the potential value and consequence of this diffusion in mind when they are developing resources. It seems likely that use of the website diffused through the course network because using the tool during out-of-class study groups allowed students to benefit from the affordances of the tool (e.g., summative feedback, multiple examples) and the affordances of the peer study group (e.g., dialogic sense-making, formative peer feedback).

Socio-material interactions spanned course spaces and time. For example, much of the in-class time in-classes A and B was focused on socio-material interactions where instructors engaged students using i-clickers, lecture slides, and collaborative problem solving. Some of these activities were required and others were optional. Some took place during course time and others did not. The academic plan, developed by the instructor in each lecture, distributes work across space, time, and individuals. The responsibility for that work, and the relevance of it to a students' intrinsic interest and personal goals, informs its uptake as part of course-work.

Outcomes. Some of the outcomes that stem from course-work engagement are unintentional byproducts of interaction. These outcomes include new and revised beliefs, new and revised relationships, and new and revised study strategies. Course-work engagement leads these

outcomes. For example, students changing relationships may be a result of their participation in out-of-class study groups as part of their course-work engagement.

Results suggest that changes in belief states relating to expectations and values for the course are significantly related to changes in course grades during the semester. Changes in these beliefs (such as attainment and utility value) may result in new course expectations and values as the semester ends. Such changes, especially changes in course beliefs, may have an impact on future course-work as well as aspirations and long terms goals.

The salience of intrinsic and utility beliefs further suggests that identities related to academic work, like an identity as a future engineer or scientist, may be emerging through course-work. Other scholars have taken up the idea of academic identities and their relationship to persistence (e.g. Hurtado, Newman, Tran, & Chang, 2010; Pierrakos, Beam, Constantz, Johri, & Anderson, 2009). As the framework above suggests (table 27), there may be emergent identities that students leave the course with in addition to their academic performance assessment. This study adds further evidence to the notion that interdependencies exist around course beliefs, social identities and academic identities that merit further exploration, especially as it relates to course-work.

Through participation in course-work students may acquire new relationships or they may add a new, academically focused dimension to an existing social relationship. Both kinds of relationships could facilitate accessing the kind of social and cultural capital that supports persistence within STEM and throughout students' undergraduate careers. The ability to cultivate socio-academic relationships is important because it prepares students for cultivating professional workforce relationships and contacts. Maintaining healthy relationships with the people who help you engage in collaborative problem solving is important for innovation (Subramaniam & Youndt, 2005), and students would benefit from capitalizing on opportunities to cultivate those skills.

Students also leave the course with a record of their academic performance. The importance of a final course grade, no matter how crude a metric it can be, should not be downplayed in STEM fields where it signals, rightly or not, a student's readiness for future opportunities. It is difficult, for example, for students in engineering fields to be competitive for summer internships if their performance in course-work is below average. Students in large lecture hall courses, especially pre-requisites, may therefore feel they are in competition with others for their grades.

There is some evidence to suggest that students' changing beliefs might be related to changing academic and professional identities. As the importance of the course relative to their future goals increased, students' performance in the course tended to decline. This might be a result of shifting academic identities, say from an unknown major to a physics major or from a future materials engineer to a student who is uncertain about their path. Further research is needed to explore the relationship among changing academic identities and kinds and levels of engagement in large science courses. Additionally, researchers should explore how course networks, especially out-of-class study groups, function to support (or deter) a variety of learning outcomes for students including knowledge acquisition, academic performance, and peer instrumental and social support.

Course-work engagement is a process that has behavioral, affective, and cognitive dimensions that are mediated through a student's interactions with course resources, peers and instructors, and that are motivated by that student's expectations and desires regarding academic achievement. Students enter a course with beliefs about the intrinsic and attainment value of the course, existing social relationships, and different levels of academic preparation and technological proficiency. Each student has individual experiences with STEM course-work and navigating campus life that inform how they will eventually approach the work of the course. Students develop an approach to course-work that is shaped by the instructor's academic plan and by the instructional activity system. Course-work engagement emerges as the students enrolled in a course make

decisions about what activities to engage in, what resources to use, and with whom to interact on course matters. The relationships that students form in a course create a network through which resources and knowledge can flow. Students who are disconnected from course networks might need to engage in different practices to access similar resources.

Implications for future research. This study highlights the limitations of the current approaches to defining and studying student engagement in the field of higher education. Studies that employ engagement as a broad construct for examining undergraduate participation in academic and social life rarely identify the specific contexts or interactions that facilitate or deter students' engagements, and often these studies thus lose focus on what happens within courses and classrooms. To understand students' experiences and their learning, it is not enough to simply assess whether they participate, are involved, or engaged. Scholars need to assess *what* students are doing in their courses. What strategies and resources do students adopt? How do they use these strategies and resources? Why do they choose and configure resources and strategies in particular ways? Studies also need to examine how students combine social resources, that is, peer relationships, with material resources to support their course-work engagement.

In this study, I have started to sketch a framework for course-work engagement in large science lecture courses, identifying specific relationships and interactions that can produce variations in course-work engagement and academic performance. In this section, I identify implications from my findings that suggest areas for future scholarly inquiry. These are identified in boldface in table 28.

Table 28. Course-work Engagement with implications for future research

Level of Analysis	Person Influences	Interactions	Environmental Influences	Outcomes
Individual	Course Beliefs Social identities (e.g. gender, citizenship) Affective Academic Beliefs	Socio-academic behavioral engagement * <div style="border: 1px solid black; border-radius: 15px; padding: 5px; width: fit-content; margin: 0 auto;">Course Network</div>		Learning Academic & Professional Identities Socio-academic Relationships Academic Performance
Course	<i>Classroom Climate</i>	[Interactive] Resource Engagement	Course Time Course Space Instructional Activities Assessment Activities	
Institution	<i>Campus Climate</i>	Membership in exogenous networks Co-enrollment in other courses	<i>Space/Time on campus</i>	

Based on my proposed framework, there are four domains of influence scholars should consider in studies of course engagement in large science courses: personal influences, interactions, environmental influences, and outcomes. These influences are operationalized at different levels of analysis including the individual, the course, and the institution. In the next section, I walk through each domain across the three levels of analysis to highlight future areas of research.

First, in addition to course beliefs and social identities, scholars should pursue personal influences at the level of the individual and the campus. On the individual level, the relationship between affective academic beliefs and course-work engagement deserves more attention. The slice of affective academic beliefs that I focused on—students’ perceptions that they are connected to and valued by their peers in the class—was not significantly related to either course-work engagement or performance. Other forms of affective belief like boredom, math anxiety, or feeling connected to the instructor, however, might have more salient influences on the development of course-work engagement.

On the institutional level, campus climate may play a role in how individuals develop and choose among course-work engagement strategies. There is substantial evidence to suggest that campus climate can influence degree completion and active participation in campus life (e.g. Museus, Nichols, Lambert, 2008). Campus climate also appears to influence students' pathways through specific academic programs, especially for students who are underrepresented in a field/discipline (e.g., Cole & Espinoza, 2008). Yet, the role that campus climate might play in engagement in an individual course is unclear. Students' perceptions of campus climate, like other beliefs, may shape engagement with peers, and may change (and become more salient) over time. A challenge for future research is to operationalize students' experiences and perceptions of campus climate in the context of specific courses. Researchers might incorporate different measures of campus climate into studies of course-work engagement (e.g., perceptual, observational, compositional), and/or focus on the experiences and perceptions of specific student subpopulations within specific institutional contexts (such as pre-dominantly white institutions or Hispanic serving institutions) to understand whether and how larger campus climates might influence engagement (and ultimately, learning).

The second domain of influence is interaction. For example, although about half of the students in this study did not participate in out-of-class study groups, social influence appeared to play a significant role in shaping course-work engagement. When students collaborated in out-of-class study groups, use of the practice problem website diffused through collaborative relationships such that students adopted the higher levels of practice problem website use of their peers. Students who were disconnected from the network did not change their behaviors in similar ways—in fact, they generally decreased their use of the practice problem website. Course-work engagement is—potentially—an interdependent phenomenon, driven by the individuals and resources with whom a student interacts. The extent to which study strategies are diffused through social interactions is not

well understood. Future research that considers the impact of social context and social interaction on the development of postsecondary students' study practices is needed.

This study built upon the theoretical foundations of self-regulated learning theory and expectancy value theory. The emerging course network identified in my analysis provides evidence that the social context of the classroom can influence students' ability to enact their goal-oriented behavior. Some students appeared constrained by network homophily or by the requirements of the instructional system as laid out by the instructor. This extends our understanding of course ecologies by illustrating how students' goal-oriented behavior in a large lecture course can be influenced by the instructional activity system of interactions among individuals and artifacts. Existing research suggests that interacting with individuals may have an immediate impact on broader campus participation- e.g. Kahu, 2013), but the proximal and distal influences of socio-academic interactions with peers and artifacts on students' long-term outcomes like persistence, professional identity development, and cognitive development is unclear.

This study suggests that scholars of undergraduate learning environments might consider the utility of mapping salient socio-material interactions within the activity system of the large lecture course. Activity theory and activity systems provide a methodological apparatus for thinking about community, cultural rules and norms, instructional practices and outcomes. Examining practice with a "minimal meaningful context" like a course (Kuutti, 1996, p. 26) by incorporating analysis of the use of technological artifacts and the organization of work (e.g. instruction and learning) into studies of course-work allows connections to be made among the individual influences identified in this study through observation and quantitative analyses. Such an approach, referred to as an activity system (Ludvigsen, et al., 2003), identifies the real-life web of activities through which social action is mediated by durable objects (Kuutti, 1996).

In activity systems, the mental and the material are connected. By analyzing the activity systems, we can connect the micro-process of individual goal oriented action and the macro-process of collective activity. Activity systems are composed of “an object, subject, mediating artifacts (signs and tools), rules, community, and division of labor” (Engeström, Miettinen, & Punamaki, 1999, p. 9). The subject in the activity system is the agent who drives practice (Engeström, et al., 2007). The object is the focus of the collective work in the system (Engeström, et al., 2007). Tools refer to the material forms used as part of practices in the system (Engeström, 1990). Rules are explicit and implicit, guiding practices and determining who is part of the activity system (Engeström, Miettinen, & Punamaki, 1999). Community is the collection of human agents who contribute to practices in the activity system (Engeström, et al., 2007). Mapping the results of this study onto an activity system is beyond the scope of this dissertation, but I can envision fruitful future research that takes up the challenge of identifying socio-material interactions in different instructional and institutional contexts. Additionally, the actual goals of the study groups in this research are unclear. Students may be gathering to prepare for academic assessments or they may be working together to develop a rich complex understanding of the physics material (or both). Future research could focus on the goals of these groups to better understand how course activities are organized and managed by out-of-class study groups.

The impact of students’ institutional-level interactions is well documented in other literature on college students’ development and learning (see Mayhew, Rockenbach, Bownman, Seifert, Wolniak, Pascarella, & Terenzini, 2016 for a comprehensive discussion). On the survey, students reported membership in campus groups like the marching band, Greek life, and student organizations that had the potential to influence who they worked with in the course. The relationship between groups exogenous to the course and out-of-class study groups merits further investigation. Similarly, students may be building a social network of information and social support

resources by focusing on peers who were co-enrolled in other courses in the same semester. Cohorts of co-enrolled students offer students an easy site for intervention and targeting help resources. How these groups function to support (or not) academic success is worth exploring.

Differences among institutional types can significantly reconfigure how space and time ‘on campus’ and ‘in-class’ are experienced. For example, how might the results of this study look different at a commuter institution, at a purely online institution, at an urban institution? How do institutional structures and geography change the ways that students approach socio-academic interaction? How might virtual classrooms result in different study and help seeking strategies?

There are a few potential outcomes of course-work engagement that are suggested by the results of this study that require further research. First, in this study, I focused on academic performance, but I did not investigate what students learned in the courses and what role socio-academic interactions and technology use played in the learning process. The role of course-work engagement in learning requires further systematic study in large science lecture courses. Second, exposure to the mechanics curriculum might facilitate or deter the development of future professional and academic plans. Given the salience of social identities in the formation and maintenance of socio-academic interactions, further attention to the professional and academic identities that extend from participation in the course are needed.

The findings in this study also suggest some specific future research projects. First, investigations of how minoritized students (women, students of color, international students) experience -- and make sense of their experiences -- in the socio-academic network of large undergraduate lecture halls are needed. This research could build on the emerging literature on classroom climate in post-secondary education (e.g. Zumbrunn, McKim, Buhs, & Hawley, 2014). How does the classroom environment (and climate) influence the interactions of minoritized

students? When and how might they be excluded from course networks? When, how and why might they self-segregate into homophilous groups? When and why might they become social isolates? The results of this research suggest that exclusion, rather than self-segregation is occurring because women and international students who attempted to participate early on were unlikely to be in relationships that lasted throughout the course. That is, they reported relationships on the first survey, their partners did not report those relationships on the first survey, and neither student reported a relationship on the second survey. How and why these relationships end is an important strand of future research, especially for scholars interested in-classroom equity.

Second, investigating the role of social networks in shaping course engagement in different disciplinary and institutional contexts is crucial. I conducted the pilot study for this research in a physics classroom at a commuter institution, and found different salient influences on network tie formation (albeit using a somewhat different survey instrument and analytical approach). Given the importance of social identity and social context revealed in this study, it is important to study how influences on course-work engagement might change in-classrooms with different configurations of social identities and in different classroom, disciplinary and institutional contexts. If classrooms include more women students, would the same preference for gender homophily be present in the network? How does – or doesn't – racial/ethnic identity influence course and lecture section level network formation across academic disciplines and in institutions with particular compositional diversity? In this study of a physics classroom in a large university, there were so few Black and Latinx students that I could not effectively account for them in the modeling process. A more racially diverse course enrollment might result in different network dynamics. In the five physics courses I have done observations, the resulting course network has contracted over time. Is this true of course networks in other science and engineering disciplines? What about courses with different instructional approaches (such as classes that assign groups or courses with less in-class interaction)?

Third, systematic study of how students' social and academic relationships change within a course and across an undergraduate career is needed. A small body of literature investigates the role of peers on persistence in undergraduate education, and there are many studies within disciplines that study peers' impacts on academic performance in the classroom (e.g. Freeman, Eddy, McDonough, Smith, Okoroafor, Jordt, & Wenderoth, 2014; Prince, 2004). Scholars need to knit this work together and undertake rigorous empirical work that looks across instructional contexts and considers these questions over time.

Most of these studies use cross-sectional data, noting the lack of temporal data as a methodological limitation. This, however, is more than a limitation in studies of persistence; it is a design flaw. To truly understand persistence, we must understand its temporal dimension as well as how it is affected by the larger socio-cultural contexts of disciplines and campuses. Similarly, we need to unpack how students' social networks (and the social capital that students can draw from them) may change over time. This work is necessary if we want to understand what promotes access, equity, and persistence in STEM majors.

This need to understand and theorize how time functions in the experiences of undergraduate students extends beyond persistence, however. Scholars need to engage in research that takes time seriously as an explanatory influence. This means examining growth and change week to week, semester to semester, and year to year. One of the affordances of learning analytics data is the potential to harness substantial amounts of temporal data that can be paired with validated cross-sectional psychometrics that could contribute substantially to our understanding of student success.

The findings from this study should also encourage further research into network formation among college students. Combining research approaches from network science, the science of team science, and peer relationship studies, scholars might provide new insights into how course networks

form, and what impact these structures might have on academic performance. As I noted above, maintaining healthy relationships has a variety of benefits for individuals (Christakis & Fowler, 2009), and individuals who can maintain multiplex relationships (that is relationships that have multiple social dimensions like friendship, professional connections, and shared interests) are able to access more diverse forms of social capital.

Finally, the results of this study indicate the need for more research of the social dimensions of adoption and use of digital instructional technologies. Efforts to develop and spread the use of these technologies have not been informed by research on how they are used by students. These technologies are inserted into study practices in a way that current adoption models cannot account for (see Brown, 2016 for an incisive critique). Specifically, adoption models are susceptible to a focus on the individual that overlooks the salience of the community and social interaction for the development of individual practices. If instructors continue to develop and implement personalized learning technologies, they need to understand and design tools that reflect students' interdependent academic and social lives. This is in addition to the rigorous evaluation of the impact of instructional technologies on student success, which fail to keep up with the rapid pace of technological innovation.

Implications for practice. A few implications for teaching and the design of instructional technology for large lecture courses can be drawn from the results of this study. First, instructors should pay attention to the social context in which their teaching occurs and how students' social identities shape their educational experience. Organically forming course networks reflect the biases of the students in a course, and are likely to be shaped by the demographic majority in both the course and the institution. The most effective way to address this is immediately unclear, without putting the burden of finding and managing peer interactions in in-class and out-of-class groups on women, Students of Color, and international students who are already underrepresented. However,

occasionally using activities that require students to randomly sort might at least allow students to encounter each other in unexpected ways.

Tools designed to be used in the classroom should reflect the intentions of the instructors and they should be studied and improved as instructors understand how students adopt the tool as a study resource, especially alongside other tools. For example, a significant limitation of the practice problem website was that it did not provide feedback about what students did right and wrong for a given problem, so many students focused on other material resources in the class. If designers of instructional technologies want to encourage adoption by students, they need to develop tools (and accompanying resources) that help students and instructors understand the different ways that a technology might be effectively used.

This study also suggests some design implications for large science lecture courses as well. By incentivizing specific practices for class preparation, the instructor potentially loses out on the benefits that flow from intrinsically motivated study behaviors. It may be that instructors are simply uninterested in producing the kind of variation that allows for interest driven learning. This is not a problem, *per se*, but it is a limitation of current course designs. The tradeoff here is a classic problem in large lecture courses—personalization requires more effort, but the scale of the course makes designs with substantial variation potentially unmanageable. There are some promising approaches that produce personalized learning pathways. For example, instructors might incorporate gameful pedagogy (where participation is driven by the interest of the individual in completing a task rather than the assignment of objectives to be completed) into their classroom to allow students to explore different approaches to learning, allowing students to capitalize on forms of assessment that match their interests and goals (Holman, Aguilar, Fishman, 2013). The results of this study suggest that students' adoption of these pathways might diffuse through social relationships.

Conclusion

The conceptual framework I outline in this study reflects what Gourlay (2015) calls “the emergent, contingent, and restless” character of students’ engagement in their course-work (p. 404). Students possess agency to carve out their path as they develop strategies and practices to achieve their course goals. Yet, this agency is directed through course infrastructures like curriculum, assessment practices, and the community of relationships that form around the course. The revised conceptual framework that I developed based on the literature and the results of this study needs to be validated and tested in other instructional contexts, across disciplines, and among different institutional types.

Based on this research I identify two essential influences that I believe should be the core focus of future research on course-work engagement. First, the influence of interaction among students, between a student and instructor, and between a student and instructional tools should cut across instructional, institutional, and disciplinary contexts. Each form of interaction will be, in turn, shaped by local conditions. Second, the progression of time has historically been undertheorized in studies of undergraduate course-work engagement in large science lectures. Time played a substantial role in how students approached the course. Students that built momentum, who clarified effective strategies had greater academic success than students who were continued to refine their course-work strategies later in the semester. Designing and improving study tools that provide students feedback about their strategies—that offer formative and summative information early on in the course—seem like an important next step for research and practice.

What I present here I believe is sufficiently flexible to guide instructional design and student-level interventions. I hope future researchers will pick up the challenge to design practice interventions that build on the affordances of students’ social relationships and their use of instructional technology. The diffusion of technology use through social relationships is a potential boon for developing personalized educational resources. To truly capitalize on this opportunity,

instructional and educational technology designers should consider the power of creating learning technologies that have collaborative and social components. The results of this study might look substantially different if the focal technology offered students the opportunity to collaborate.

I also hope instructors will respond to the framework I develop by reflecting on how their instructional practices may or may not address the salient role of race, gender, and culture in active learning classrooms. In addition to this study, recent research in undergraduate introductory biology courses also determined that students were likely to sort based on shared social identities and socio-demographics (Freeman, Theobald, Crowe, & Wenderoth, 2017). Implementing an instructional intervention designed to boost engagement without awareness of the potential to reproduce marginalizing forces will not effectively engage all students, especially in-classrooms where some students are substantially underrepresented.

This study represents two years of design, research, and contributions from many individuals. I look forward to continuing to develop the framework I present here, and to investigating the questions I have outlined above.

Appendix A. Factor Scale Loadings for Expectancy Value Scale

	Competency Beliefs	Attainment Value	Intrinsic Value	Utility Value	Perceived Cost
If you were to order all of the students in this class from the worst to the best in science, where would you put yourself? (Top 5%-Bottom 25%, five options)	X				
Compared to other students, how well do you expect to do in this course? (5-point scale where 1= Much worse and 5= Much Better)	X				
Is the amount of effort it will take to do well in this class worthwhile to you? (7-point scale where 1 = Not at all worthwhile and 7 =Very worthwhile)		X			
I feel that, to me, being good at solving problems, which involve science or reasoning scientifically is: (7-point scale where 1= Not all important and 7= Very important)		X			
How important is it to you to get a good grade in this class? (7-point scale where 1= Not all important and 7= Very important)		X			
In general, I find working on assignments/studying for this class: (7-point scale where 1=Very boring and 7=Very interesting)			X		
The lectures I attend for this class are: (7-point scale where 1=Very boring and 7=Very interesting)			X		
How useful is this class for what you want to do after you graduate and go to work? (7-point scale where 1=Not at all useful and 7= Very useful)				X	
How useful is what you learn in this class for your daily life outside school? (7-point scale where 1=Not at all useful and 7= Very useful)				X	
Considering what I want to do with my life, taking this class is just not worth the effort (7-point scale where 1 = Strongly disagree and 7 = Strongly agree)				X	
I worry that this class will take time away from other activities that I want to pursue. (7-point scale where 1 = Strongly disagree and 7 = Strongly agree)					X
I would be embarrassed if I found that my work in this class was inferior to that of my peers (7-point scale where 1 = Strongly disagree and 7 = Strongly agree)					X
I'm concerned that the time I dedicate to this class may affect important relationships in my life (7-point scale where 1 = Strongly disagree and 7 = Strongly agree)					X

Chi-square is 40.95 on 13 degrees of freedom. P<0.5

Appendix B. Factor Scale Loadings for Classroom School Community Index

	Academic		Social	
	Campus	Class	Campus	Class
Scale: (1=Strongly Disagree to 7=Strongly Disagree)				
I feel that students in this course care about each other.				X
I feel connected to others in this course				X
I trust others in this course.				X
I feel that I can rely on others in this course.				X
I feel confident that others will support me in this course.				X
I feel that I receive timely feedback in this course		X		
I feel that I am given ample opportunities to learn in this course.		X		
I feel that my educational needs are not being met in this course.		X		
I feel that this course does not promote a desire to learn.		X		
I have friends at this school that I can tell anything.			X	
I feel that I matter to others at this school.			X	
I feel close to other at this school.			X	
I regularly talk to others at this school about personal matters.			X	
I feel that I rely on others at this school.			X	
I feel that this school satisfies my educational goals	X			
I feel that this school gives me ample opportunity to learn.	X			
I feel that this school does not promote a desire to learn.	X			
I share the educational values of others at this school.	X			
I am satisfied with my learning at this school.	X			

Chi-square is 30.22 on 11 degrees of freedom, $p < 0.01$

Appendix C: Informed Consent Document

Understanding Student Course-Work Engagement in Large Lecture Hall Courses

Michael Geoffrey Brown
Doctoral Candidate, Center for the Study of Higher and Postsecondary Education
School of Education, University of Michigan
mbrowng@umich.edu

Michael Brown invites you to participate in a research study about how students prepare for class in large lecture hall courses. You have been selected to complete this survey because you are enrolled in Physics 140 during the Fall 2016 semester at the BLINDED. The purpose of this study is to understand the impact of students' studying in groups to prepare for class.

This study is part of a dissertation project supervised by Dr. Lisa Lattuca, Professor of Education at the School of Education, University of Michigan, Ann Arbor. Questions about the project can be directed at any time (now or in the future) to the study coordinator, Michael Brown at mbrowng@umich.edu or to Dr. Lattuca at llatt@umich.edu.

If you agree to participate in the study you will be asked to complete two surveys, one today and another on TBD. Both of these surveys will be provided to you through your university email address. Each survey should take about 10 minutes to complete. You will receive extra credit in the course for completing each survey. You do not need to share the results of your survey with the researcher to receive the extra credit. You will be provided the opportunity to complete the survey, and then on the final page you will be asked if you would like to share your responses and provide access to other data sources to the researcher. At the end of the survey you will be asked if you are willing to provide the researcher: 1) your score on the University Math Placement Exam (or an equivalent score such as the ACT/SAT) from the University Registrar. 2) Your log-ins for the Canvas Learning Management System, 3) the class online homework system, and 4) the Problem Roulette application will be provided to the researcher. 5) Your grade on homework assignments and exams will also be provided to the researcher.

There are few risks associated with participation in this study. However, breach of confidentiality is possible. The researcher will immediately de-identify any data you provide (or that is provided on your behalf). Only the researcher will have access to your data, which will be stored on a password-protected server. No identifiable information will be shared as part of any presentation or publication based on this research.

Although you may not benefit directly from this study, the results of this study could improve instruction at the BLINDED. You will be asked to identify the names of other students you work with in this class. The researcher will keep all information provided including the peers you identify in strict confidence

Confidentiality

We plan to publish the results of this study, but will not include any information that would identify you. To keep your information safe, the researchers will assign you a study number and your name will not be attached to any data.

The researchers will retain the data for 2 years at which point the data will be deleted. The data will not be made available to other researchers for related studies.

Participating in this study is completely voluntary. Even if you decide to participate now, you may change your mind and stop at any time. You may also skip any question in the survey you do not wish to enter.

If you decide to withdraw early the information or data you provided will be destroyed.

If you have questions about your rights as a research participant, or wish to obtain information, ask questions or discuss any concerns about this study with someone other than the researcher(s), please contact the University of Michigan Health Sciences and Behavioral Sciences Institutional Review Board, 2800 Plymouth Rd. Building 520, Room 1169, Ann Arbor, MI 48109-2800, (734) 936-0933, or toll free, (866) 936-0933, irbhsbs@umich.edu. (

The e-research number for this study is HUM00116041

By click 'Yes' below, you are agreeing to be in the study. You will be given a hard copy of this document for your records and one copy will be kept with the study records. Be sure that questions you have about the study have been answered and that you understand what you are being asked to do. You may contact the researcher if you think of a question later.

- *Yes, I agree to participate in the study.*
- *No, I do not wish to participate in the study, but I do wish to complete the survey for extra credit.*
- *No, I do not wish to participate in the study, and I do not wish to complete the survey for extra credit.*

Type your name:

+Please click here to receive a copy of this document to print for your records.

Appendix C. Additional Survey Questions

Please select all the statements that are true for your approach to this course.

- I prefer to work alone when preparing for exams and homework assignments.
- I collaborate with other students when completing homework assignments.
- I collaborate with other students when preparing for exams.



Please name up to five people you collaborate with on coursework for Physics 140.

First Name

Last Name

For the student you identified:

	Please select the answer that most accurately reflects how you work together on course tasks.		
	I helped my partner more.	We helped each other equally.	My partner helped me more.
$\$ \{q://QID6/ChoiceGroup/SelectedAnswers/1\}$ $\$ \{q://QID6/ChoiceGroup/SelectedAnswers/2\}$	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

For the student you identified, please check all the boxes that are relevant for your relationship.

- Knew before course
- Work on homework together
- Study for exams together

Would you like to add an additional student?

- Yes
- No

Please enter the names of any students you collaborate with to prepare for this course who you could not find in the roster:

How would you rate your technical skills for this course? (e.g. accessing online course resources, using the Python programming language for lab assignments)

- My technical expertise was not quite what I needed to do well in this course.
- My technical expertise was sufficient to do well in this course
- My technical expertise exceeds what is required to do well in this course

In a typical week, how many hours do you spend on: (if you work more than 10 hours, please select 10)

- _____ Mastering Physics homework system
- _____ Preparing for lab
- _____ Preparing for lecture
- _____ Preparing for exams

Are you (please select all that apply):

- African American/Black
- Asian/Pacific Islander
- Hispanic/Latino/a
- American Indian/Native American
- Caucasian/White
- Middle Eastern
- Foreign national (i.e. citizen of another country)
- Naturalized U.S. citizen
- Other (please specify): _____
- I prefer not to respond

How would you describe your gender/gender identity (please select all that apply):

- Woman
- Man
- Transgender/Genderqueer
- Other (please specify): _____
- I prefer not to respond

When you entered the University of Michigan, were you?

- A first time college student
- A transfer student from a community or two-year college
- A transfer student from a four-year institution

What other course-work in Physics have you completed? (Please select all that apply)

- This is my first Physics course
- High School Physics
- Advanced Placement (AP) Physics AB
- Advanced Placement (AP) Physics BC
- Physics at a Community College
- Physics at another university
- Physics at the University of Michigan (Please specify the course): _____

What is the highest level of Math course-work you have completed?

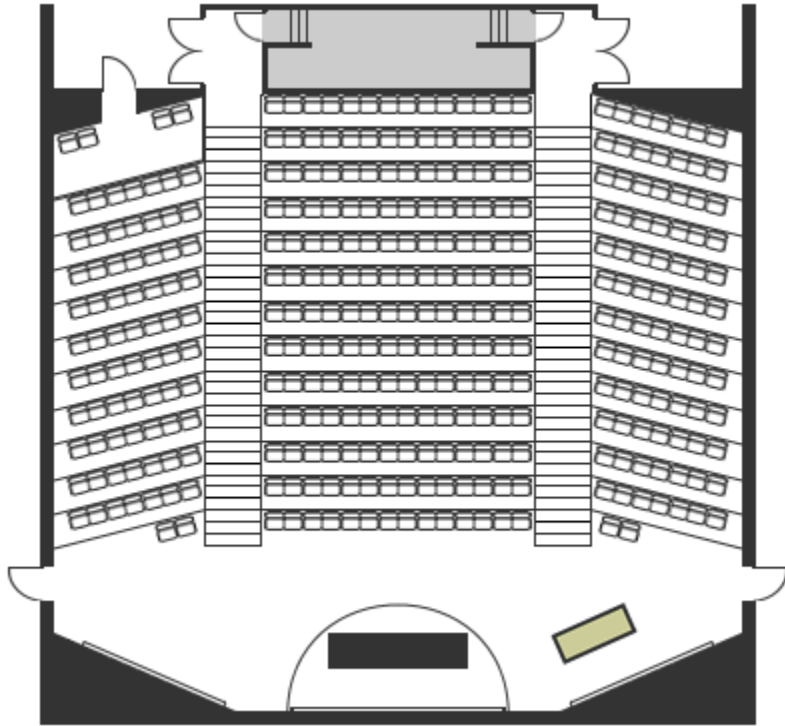
- Pre-Algebra
- Algebra
- Pre-Calculus
- Calculus 1
- Calculus 2 or higher
- Other (please specify) _____

In a typical week, how many hours on average do you spend:

- Working for pay: _____
- Preparing for all of your classes (studying, doing homework or lab work, and other academic activities): _____

What grade do you anticipate receiving in this course?

Where do you generally sit
in a lecture style classroom?
Click on the general area in
the room where you sit.



Thank you for completing the survey.

Appendix D. Stochastic Actor Based Model (SABM)

Table 29. SABM Results

Rate of Change		
Network (Dependent Variable)	1.489	0.129
Practice Problem Website Use (Dependent Variable)	1.365	0.148
	Log Odd	Standard Error
Structural Network Effects		
outdegree (density)	-9.052**	(3.471)
reciprocity	5.492***	(0.820)
transitive triplets	4.593**	(1.693)
transitive reciprocated triplets	-3.720	(3.921)
3-cycles	-1.864	(3.434)
indegree - popularity (sqrt)	-1.155	(0.823)
indegree - activity (sqrt)	-0.428	(1.129)
outdegree - activity (sqrt)	-0.625	(2.494)
Social Identity Influences		
Receiver: Underrepresented	-1.258	(1.099)
Sender: Underrepresented	-0.006	(1.217)
Homophily: Race/Ethnicity	-0.276	(1.055)
Receiver: Men	0.221	(0.379)
Sender: Men	-1.298**	(0.479)
Homophily: Gender	0.718†	(0.416)
Receiver: International Student	-0.621†	(0.322)
Sender: International Student	4.523*	(1.891)
Receiver: Friend	-0.312	(0.375)
Sender: Friend	1.461*	(0.714)
Academics and Course Level Influences		
Homophily: Undergraduate College	0.029	(0.391)
Homophily: Undergraduate Year	0.414	(0.366)
Homophily: Lecture Seat	0.115	(0.372)
Homophily: Lab Section	0.960*	(0.443)
Homophily: Lecture Section	3.633**	(1.393)
Similarity: Practice Problem Use	0.424	(0.610)
Similarity: Academic Performance	0.272	(0.881)

Appendix D continued.		
Sense of Community		
	Log Odd	Standard Error
Receiver: Campus Academic Community	0.270	(0.162)
Sender: Campus Academic Community	0.088	(0.310)
Receiver: Classroom Academic Community	-0.173	(0.189)
Sender: Classroom Academic Community	-0.172	(0.257)
Receiver: Classroom Social Community	-0.126	(0.175)
Sender: Classroom Social Community	-0.235	(0.265)
Receiver: Campus Social Community	-0.137	(0.284)
Sender: Campus Social Community	-0.235	(0.265)
Practice Problem Website Use		
linear shape	-0.907***	(0.158)
quadratic shape	0.666***	(0.066)
isolate (no collaborators reported)	-0.004	(0.212)
average use of problem application by peers	0.050	(0.234)
Effect from technical proficiency factor	-0.069	(0.199)
Effect for Black, Latinx, Native American & Native Hawaiian students	0.294	0.237
Effect for Women	-0.117	(0.175)

† p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001;

Appendix E: Results for Grade Change

Table 30. Fixed Linear Model¹

	Coefficient	Standard Error
Practice Problem Website Use	0.667980	0.592358
Sense of Community Factor Scales		
Campus Academic Sense of Community	-0.056466	0.496011
Classroom Academic Sense of Community	0.285513	0.371617
Campus Social Sense of Community	0.177596	0.443583
Classroom Social Sense of Community	0.061544	0.383531
Expectancy Value Factor Scales		
Attainment Value	-0.632187	0.596923
Competency Beliefs	0.332629	0.358971
Perceived Cost	0.556756	0.515347
Intrinsic Value	1.210770	0.519044
Utility Value	-0.885968	0.493411
Network Participation		
Changing In-Degree	0.126934	0.551372
Changing Out-Degree	-1.632638	0.530764
Demographics		
Effect for Women	-2.034348	0.922105
Effect for time	2.320932	0.787233
<i>Total Sum of Squares: 20334 Residual Sum of Squares: 18606</i>		
	R-Squared: 0.084992	Adj. R-Squared: -0.88859
F-statistic: 3.00554 on 14 and 453 DF, p-value: 0.00019374		

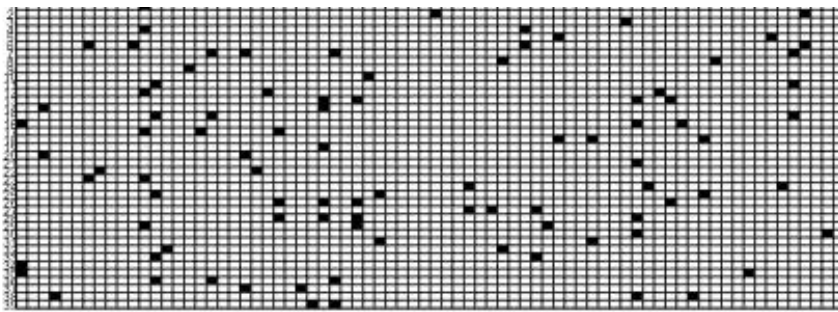
Significance codes: *** 0.001 ** 0.01 * 0.05 . 0.1 ' 1

¹Outcome is change in student's grade between the period after the first exam and the final exam. Out of 100 possible percentage points.

Appendix F. Initial Results from Pilot 1 (from Brown, 2015).

Based on the first pilot survey, I developed a socio-matrix and generated visualizations of collaborative ties in the course network (figure F1). I cross-referenced self-reported ties against observed collaborations in the course to develop the final network visualizations as well as to develop external individual accuracy correlation (Avila de Lima, 2015). For example, throughout the lecture, the course instructor would provide students with analytical problems to solve in self-selected groups. Using a bird's eye map of the room, I noted where students were seated and made notations about their collaborative behaviors during assigned tasks. In only one case were reported ties substantially different from observed ties, although in this specific case the reported tie was with a student who dropped the course; effectively removing that collaborator from the network.

Figure 14. Socio-matrix for Course Collaboration Network



Results of the Fall 2014 Pilot

The pilot study focused on 1) factors that predicted students' social selection of peers for participation in Peer Instruction activities, and 2) the relationship between participation in the collaborative learning network and students' academic performance. I used statistical network analysis to calculate the odds that a student would select a partner for working on collaborative

instructional activities based on an individual's demographics and academic preparation (see Table A1).

I observed little evidence that students in the Fall 2014 lecture course select partners on the basis of identity or academic preparation, the mechanisms suggested by prior literature. However, the significance of edgewise partnerships suggests that collaborative learning networks in the course had high levels of transitivity (e.g. the friend of my friend is my friend). This suggests network closure, meaning students who are connected are generally working in small cloistered groups.

Table 31. Odds of Peer Interaction (n=71)

	Lower CI	Odds Ratio	Upper CI	Wald
Edges	0.081	0.0206	0.0525	-8.12
Engineering	0.5947	0.8712	1.2763	-0.71
B Grade Group	0.811	1.3860	2.3687	1.19
C Grade Group	0.8317	1.1197	1.5074	0.75
Math Placement Exam (standardized)	0.8127	0.9317	1.0682	-1.01
Match by				
Women	0.3477	1.1565	3.8472	0.23
Men	0.8078	1.2343	1.8859	0.97
No AP Credit	0.5091	0.9160	1.6482	-0.29
AP Physics Course*	0.1493	0.3689	0.9115	-2.16
2+ AP Courses	0.3480	0.8674	2.1618	-0.30
Weighted Degree	0.2277	0.5594	1.3744	-1.26
Weighted Edgewise Partnerships**	1.2095	1.6864	2.3512	3.08
Weighted Dyad Shared Partnerships	0.9343	1.0610	1.2048	0.91
AIC	752.5	BIC	828.8	

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ + $p < 0.10$

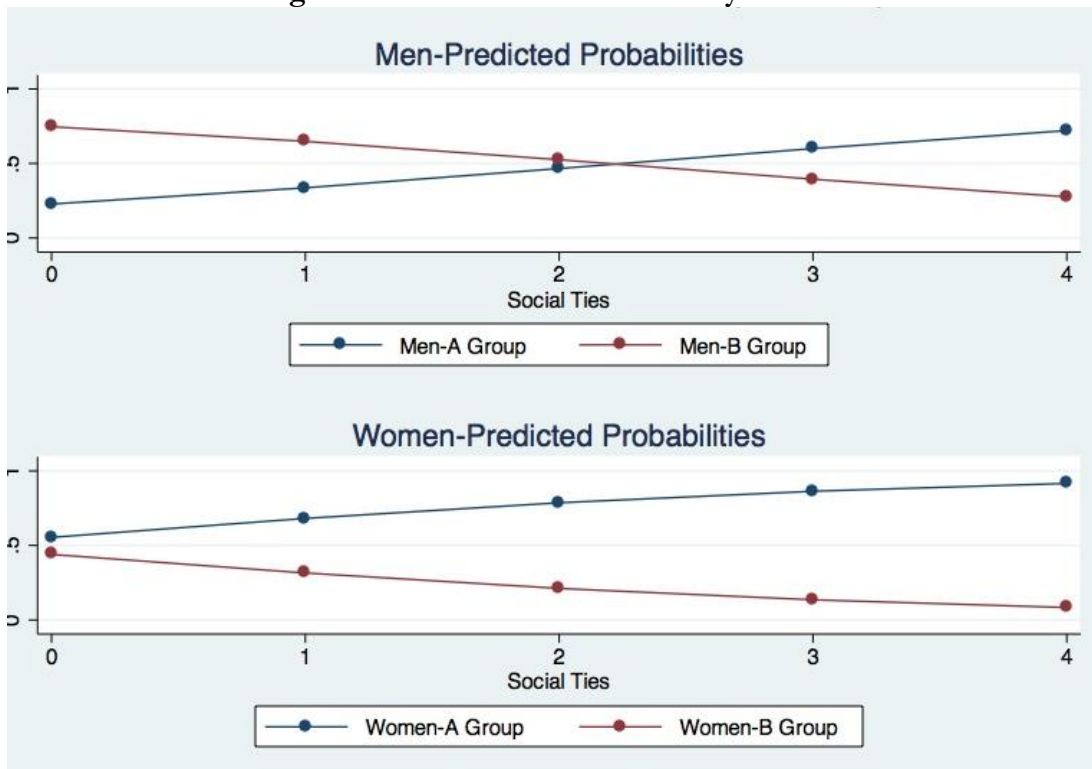
Given the small size of the network, it is perhaps unsurprising that few parameters were significant predictors of tie formation. However, during observations I noted significant peer selection by gender. Specifically, during peer programming activities where students worked in groups of four or five students, two types of groups emerged: groups were either gender segregated (one group of all women, three groups of all men) or gender integrated with one woman working with three to five

men. The confidence intervals for gender matching support this observation, as about half of the women were between 100 to 300 times more likely to match with other women and about half of the men were between 120 to 180 times more likely to match with other men. This suggests that gendered influences played an important role in groups formation, even if the parameter in the final model was not a significant predictor. Further research, in a larger class with greater diversity, might help identify the extent to which learning communities in large lecture classes are shaped by gender and racial homophily.

Clearer evidence of the influence of learning community participation emerged in students' grade outcomes (see figure F-2). Using an ordinal logistic regression model, students were placed into one of three groups based on grade performance (either they received a grade of A, B, or C and lower). As students' collaborative partner count went up, their log-odds of being in the A group increased compared to the B and C groups.

The results of this pilot study confirm the importance of peer interaction in the classroom and reveal some potential influences that shape the emergence of the classroom learning community. However, few technological resources were used in this course because of its smaller size and more intimate instructional approach. Additionally, the enrolled students were highly motivated and well prepared. A course with greater variation in academic preparation, student motivation, and demographic diversity could produce more significant results because of greater variation in outcomes. In the pilot, it was difficult to identify important influences because the only variation in outcome was between A and B students (less than five students received a C or lower). A larger sample in a more typical course (like a large introductory lecture course in physics with multiple sections of $n > 300$) could provide results with wider applicability.

Figure 15. Social Ties and Grade by Gender



Appendix G. Initial results from Pilot 2.

Table 32. Classroom School Community Index Course Form.
SOC-School

	Mean (SD)	SD	D	N	A	SA
Share the educational values of others.	3.20 (1.0)	4.8%	22.6%	26.2%	40.5%	6.0%
Satisfied with my learning.	3.26 (1.0)	6.0%	20.2%	20.2%	48.6%	4.8%
Regularly talk abouts personal matters.	3.38 (1.1)	10.7%	10.7%	17.9%	51.2%	9.5%
Have close friends at school.	3.51 (1.0)	4.8%	13.1%	19.0%	52.4%	10.7%
Feel that I matter.	3.44 (1.0)	7.1%	10.7%	20.2%	54.8%	7.1%
Feel close to others.	3.45 (1.1)	7.1%	13.1%	17.9%	51.2%	10.7%
Educational goals are satisfied.	3.29 (1.0)	4.8%	21.4%	22.6%	42.9%	8.3%
Does not promote desire to learn.	3.18 (1.1)	4.8%	25.0%	26.2%	35.7%	8.3%
Can rely on others.	3.40 (1.0)	3.6%	16.7%	26.2%	42.9%	10.7%
Ample chances to learn at school.	3.50 (1.0)	2.4%	20.2%	15.5%	48.6%	13.1%

Percent

100
75
50
25
0

Table 33. Classroom School Community Index School Form (from pilot 2)
SOC-Classroom

	Mean (SD)	SD	D	N	A	SA
Trust others in this course.	3.26 (1.12)	8.3%	15.5%	29.8%	34.5%	11.9%
Students in this course care about each other.	3.11 (1.02)	4.8%	26.2%	28.6%	34.5%	6.0%
Rely on others.	3.27 (1.11)	7.1%	17.9%	27.4%	35.7%	11.9%
Receive timely feedback.	3.11 (1.03)	4.8%	28.6%	22.6%	39.3%	4.8%
Only modest learning.	3.11 (0.97)	1.2%	33.3%	23.8%	36.9%	4.8%
Feel connected to others in the course	3.18 (1.08)	7.1%	21.4%	25.0%	39.3%	7.1%
Education needs are met.	3.01 (0.95)	4.8%	28.6%	28.6%	36.9%	1.2%
Course does not promote a desire to learn.	3.13 (0.95)	2.4%	27.4%	29.8%	35.7%	4.8%
Confident others will support me.	3.32 (1.15)	7.1%	19.0%	22.6%	36.9%	14.3%
Ample opportunities to learn.	3.15 (0.90)	2.4%	23.8%	32.1%	39.3%	2.4%

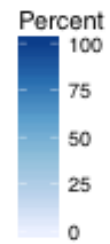
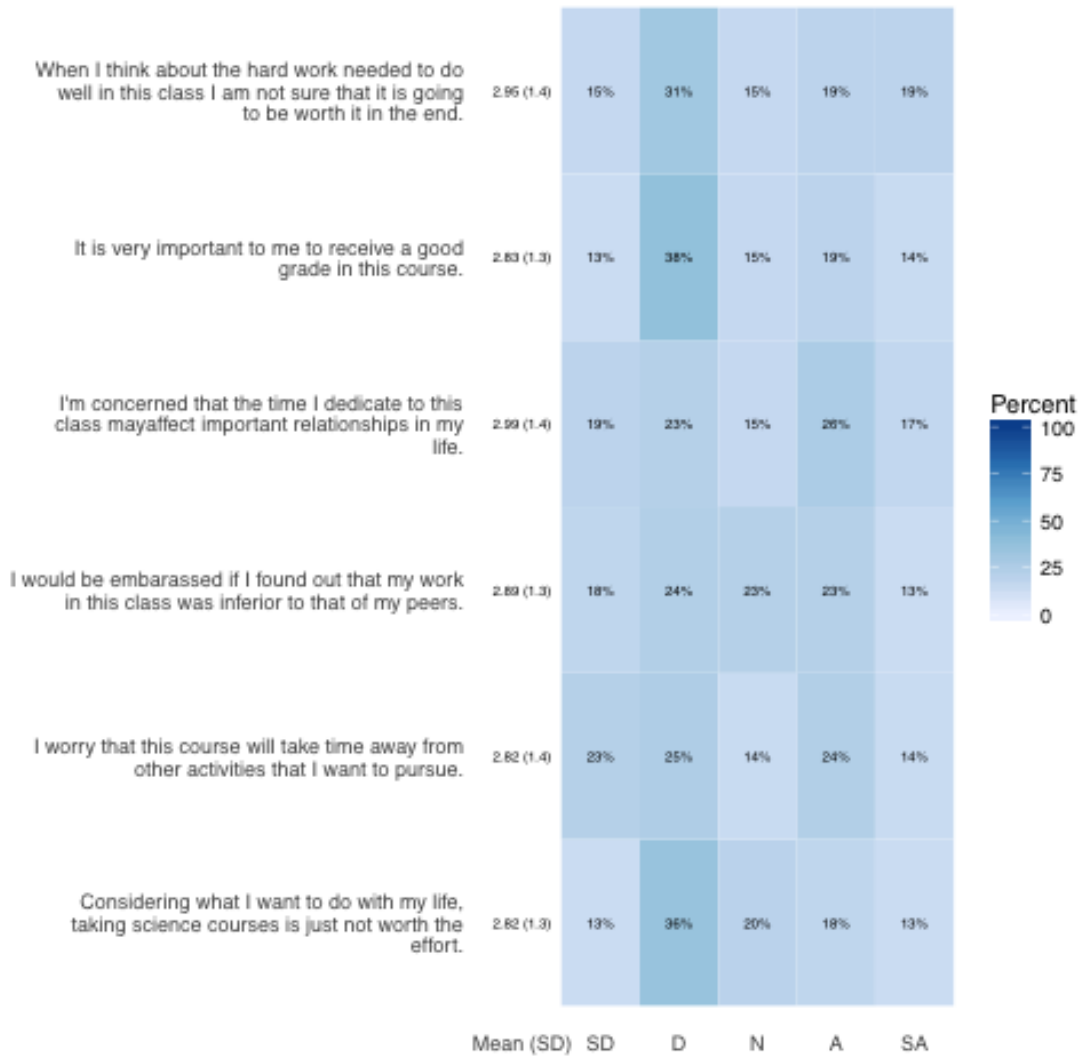


Table 34. Expectancy Value Scale (from pilot 2)

Expectancy Value Items



Appendix H. Wave 1 Survey Instrument from Pilot 2.

This survey is intended to help us understand how students learn in this course. Your individual responses to this survey will not be shared with the instructors, nor will any responses you provide have a bearing on your final grade in the course. This is survey is 'in process' so feel free to identify to the researcher anything that did not make sense or was missing at the end of the survey. Thank you for your participation! Participants in this survey will be entered into a raffle for a \$50 Amazon gift card.

What is your University of XXXX E-mail address?

(You will not receive any more communications about this research. This is simply for notifying the raffle winner).

How would you describe your race/ethnic identity (please select all that apply):

Asian/Pacific Islander African American/Black Latino
Native American White

How would you describe your gender/gender identity (please select all that apply):

Man Woman Transgender/Genderqueer

Did you attend a community college before BLINDED? Yes No

What other course-work in Physics have you completed? (Please select all that apply)

- This is my first Physics course
- High School Physics
- Honors High School Physics
- Advanced Placement (AP) Physics AB
- Advanced Placement (AP) Physics BC
- Physics at a Community College
- Physics at another university
- Physics at the BLINDED (Please specify the course):

Please indicate the extent to which you agree or disagree with each of the following statements.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
When I think about the hard work needed to do well in this class I am not sure that it is going to be worth it in the end.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Considering what I want to do with my life, taking sciences courses is just not worth the effort.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I worry that this course will take time away from other activities that I want to pursue.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would be embarrassed if I found out that my work in this class was inferior to that of my peers.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I'm concerned that the time I dedicate to this class may affect important relationships in my life.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
It is very important to me to receive a good grade in this course.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please indicate the extent to which you agree or disagree with each of the following statements.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I feel that students in this course care about each other.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that I receive timely feedback in this course.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel connected to others in this course.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that this course results in only modest learning.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I trust others in this course.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that I am given ample opportunities to learn in this course.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that I can rely on others in this course.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that my educational needs are not being met in this course.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel confident that others in this course will support me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that this course does not promote a desire to learn.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please indicate the extent to which you agree or disagree with each of the following statements.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I have friends at this school to whom I can tell anything.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that this school satisfies my educational goals.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that I matter to other students at this school.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that this school gives me ample opportunities to learn.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel close to others at this school.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that this school does not promote a desire to learn.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I regularly talk to others at this school about personal matters.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I share the educational values of others at this school.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that I can rely on others at this school.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am satisfied with my learning at this school.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please indicate the answer that most closely reflects your feelings about this course.

	Very Useless	Useless	Neutral	Useful	Very Useful
How useful is this course for what you want to do after you graduate?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
How useful is what you learn in this course for your daily life outside school?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Who do you collaborate with either 1) during class time on activities at your seat, 2) on assignments, or 3) to prepare for quizzes/exams in this class? (Please include the first and last names of up to five students. If you have difficulty recalling or do not know a partner's last name, please include as much as you can like their BLINDED or E-mail address- or ask them!) Please check the boxes that are true for your relationship.

I prefer to work on my own.

Name	Friends	Advice	Study Together
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

What is the highest level of Math course-work you have completed?

- Pre-Algebra
- Algebra
- Pre-Calculus
- Calculus 1
- Calculus 2 or higher
- Other: _____

Where do you generally sit in a lecture style classroom? (Please place an x as close as possible to your preferred seat).

Classroom Diagram Inserted Here

In general, I find studying for this class and working on assignments to be:

- Very boring
- Somewhat boring
- Neither boring or interesting
- Somewhat interesting
- Very interesting

Being good at solving problems, which involve science or reasoning scientifically is:

- Extremely Important
- Very Important
- Neither Important nor Unimportant
- Very Unimportant
- Not at all Important

If you were to order all of the students in your class from the worst to the best academically, place an x by the category where you would put yourself?	_____	Top 5%
	_____	Top 25%
	_____	Top 50%
	_____	Bottom 50%
	_____	Bottom 25%

On average, how many hours a week do you spend at work: _____ hours

On average, how long is your commute to campus: _____ minutes

What is your desired grade for Physics 151?

Is there anything in the questions above that you didn't understand (and why)? Is there anything else that should be included as a question response? Any questions that should be reworded?

Appendix I.. Wave 2 Survey Instrument from Pilot 2

This survey is intended to help us understand how students learn in this course. Your individual responses to this survey will not be shared with the instructors, nor will any responses you provide have a bearing on your final grade in the course. This is survey is 'in process' so feel free to identify to the researcher anything that did not make sense or was missing at the end of the survey. Thank you for your participation! Participants in this survey will be entered into a raffle for a \$50 Amazon gift card.

What is your BLINDED E-mail address?

(You will not receive any more communications about this research. This is simply for notifying the raffle winner).

Did you attend supplemental instruction, tutoring, or a study group for this course? Yes
No

In general, I find studying for this class and working on assignments to be:

- Very boring
- Somewhat boring
- Neither boring or interesting
- Somewhat interesting
- Very interesting

Being good at solving problems, which involve science or reasoning scientifically is:

- Extremely Important
- Very Important
- Neither Important nor Unimportant
- Very Unimportant
- Not at all Important

Please indicate the extent to which you agree or disagree with each of the following statements.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
When I think about the hard work needed to do well in this class I am not sure that it is going to be worth it in the end.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Considering what I want to do with my life, taking sciences courses is just not worth the effort.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I worry that this course will take time away from other activities that I want to pursue.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would be embarrassed if I found out that my work in this class was inferior to that of my peers.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I'm concerned that the time I dedicate to this class may affect important relationships in my life.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
It is very important to me to receive a good grade in this course.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please indicate the extent to which you agree or disagree with each of the following statements.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I feel that students in this course care about each other.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that I receive timely feedback in this course.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel connected to others in this course.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that this course results in only modest learning.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I trust others in this course.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that I am given ample opportunities to learn in this course.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that I can rely on others in this course.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that my educational needs are not being met in this course.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel confident that others in this course will support me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that this course does not promote a desire to learn.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please indicate the extent to which you agree or disagree with each of the following statements.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I have friends at this school to whom I can tell anything.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that this school satisfies my educational goals.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that I matter to other students at this school.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that this school gives me ample opportunities to learn.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel close to others at this school.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that this school does not promote a desire to learn.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I regularly talk to others at this school about personal matters.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I share the educational values of others at this school.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that I can rely on others at this school.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am satisfied with my learning at this school.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Who do you collaborate with either 1) during class time on activities at your seat, 2) on assignments, or 3) to prepare for quizzes/exams in this class? (Please include the first and last names of up to five students. If you have difficulty recalling or do not know a partner's last name, please include as much as you can like their BLINDED or E-mail address- or ask them!) Please check the boxes that are true for your relationship.

I prefer to work on my own.

Name	Friends	Advice	Study Together
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

<p>If you were to order all of the students in your class from the worst to the best academically, place an x by the category where you would put yourself?</p>	_____	Top 5%
	_____	Top 25%
	_____	Top 50%
	_____	Bottom 50%
	_____	Bottom 25%

Please indicate the answer that most closely reflects your feelings about this course.

	Very Useless	Useless	Neutral	Useful	Very Useful
How useful is this course for what you want to do after you graduate?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
How useful is what you learn in this course for your daily life outside school?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Appendix J. ERGM for Pilot 2

Exponential Random Graph Models (ERGM)

Depending on the rate of change I observe in the final data, I will (hopefully) use SABM to answer my first research question. ERGM is presented here as an alternative model in the case that insufficient rates of change are observed in the data. ERGM estimation presumes a greater level of stability and equilibrium in the data and is better suited for datasets with low rates of change

(Goodreau et al., 2009). ERGM can be easily extended to time-series estimation (TERGM). I

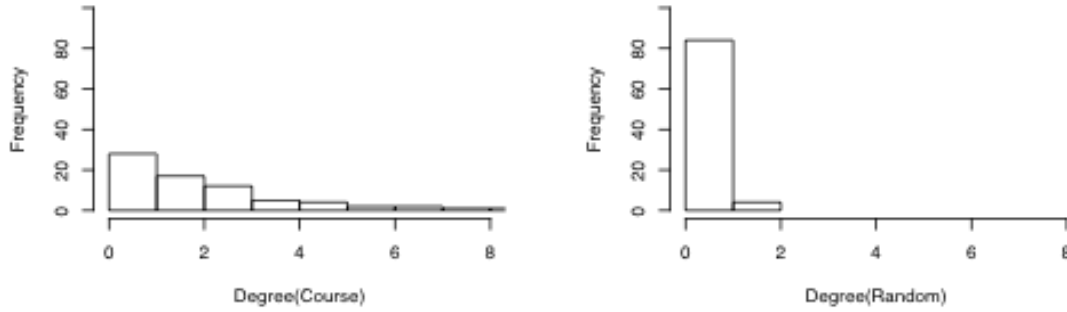
include this section here as a placeholder to familiarize the reader with an alternative approach.

Scholars have used ERGM models extensively to understand the relationship between social ties and social behaviors like information sharing, providing social support, or social selection of peers for tie formation (Harris, 2012).

ERGM assumptions.

To model a graph using an ERGM approach, an observed graph must meet three assumptions. First, the network should display non-uniform degree distribution, which suggests that individuals do not have the same tendency to form ties as a randomly generated network of the same size (Harris, 2012). As figure 6 illustrates, the observed network in the first pilot study has non-uniform degree distribution in comparison to a simulated random network of similar parameters.

Figure 16. Histogram of degrees for observed and random network (Pilot 1-Fall 2014)



Second, actors with similar characteristics should form ties more often than chance; suggesting that the network is organized by peers seeking out individuals with similar identities or experiences (or homophily; Harris, 2012). As table 6 illustrates, the matching odds of men and women in the network are substantially different from random chance.

Table 35. Odds of Same Gender Ties in the Collaboration Network (Pilot 1-Fall 2014)

	Same Gender	Mixed Gender	Total	Matching Odds
Men (n=56)	70	19	89	3.68
Women (n=15)	3	21	24	0.11

Finally, the network structure should suggest that individuals in the network tend to form ties with friends of friends (known as transitivity; Harris, 2012). Table 7 displays the distribution of triads with shared edges (either 1, 2, or 3), which are instances where transitivity is present. A census of triads (or three, connected individuals) in the pilot study network suggests that about 90 triads possessed transitive properties, which is greater than the number of triads that exhibit closure (where students in a group of three are only connected to each other; n=15).

Table 36. Triad Census (Pilot1- Fall 2014)

Triad Edges	0	1	2	3
Frequency	56300	5630	251	15
Transitivity: 0.152; Weak Census: 90 Triads				

Using Frank and Strauss’ (1986) equation for dyadic dependence, ERGM estimation assumes that individuals with no ties are conditionally independent and nodes sharing a tie are conditionally interdependent. Similarly, nodes that share no tie, but share a third node in common (e.g. A and B share no tie, but A and B are both connected to C) are said to possess dyadic dependence. This allows for the examination of network structures like edge-wise and dyad-wise partnerships. An example of the ERGM structural equation from the fall 2014 pilot is below:

$$P(Y_{ij}1 | n \text{ actors}, Y_{ij}^C) = \text{logistic}(\theta_{\text{edges}}\Delta_{\text{edges}} + \theta_{\text{AGroup}} + \theta_{\text{BGroup}} + \theta_{\text{Cgroup}} + \theta_{\text{math}}\Delta_{\text{math}} + \theta_{\text{APPhysics}} + \theta_{\text{2AP}} + \theta_{\text{NO-AP}} + \theta_{\text{LiberalArts}} + \theta_{\text{Engineering}} + \theta_{\text{male}} + \theta_{\text{female}} + \theta_{\text{GWDGWD}} + \theta_{\text{GWESPGWESP}} + \theta_{\text{GWDSPGWDSP}})$$

Where the probability of a tie between i and j actors is condition on the rest of the network (Frank & Strauss, 1986); θ is the coefficient for the log-odds of each covariate being ‘true’ for ij actors; Δ is the change in units as the variable unit increases by one (or the change statistic), and a number of covariates based on exogenous and endogenous influences. Understanding the probability of a student to engage in collaboration or to use instructional technology over time could allow the researcher to explain sources of variation in outcomes.

Data Analysis for RQ2

RQ2: How does the instructional system shape students’ engagement in peer interactions and their use of technological tools in a large lecture course?

To address my second research question, I will use observational data and descriptive network data to illustrate whether and how the classroom network evolves and how the behaviors of students in the classroom vary as a result of the instructional strategies and instructional moves used

by the course instructors. This approach draws upon visualizations of the networks as they evolve during (measured at two time periods). For each course, using a static network layout, we can observe how connections between students may change over time. These changes can also be calculated, allowing the researcher to make an argument about how collaborations increased, decreased, or held static over time. Networks can also be mapped so that students' characteristics (like their behavioral engagement with DITs) can be signaled by adding colors or shapes to the nodes. General trends in behavioral engagement will, therefore, be visible to the researcher and reader. Again, these values can also be calculated as statistical parameters. I plan to highlight any contrasts between classroom networks that arise from instructional strategies.

Appendix K: Rate of Change

Rate of Change. Students had low probabilities of making changes to their relationships or their practice problem website use between the first and final exams. Students had about 1.5 opportunities to make changes to their network, on average (rate=1.489 (0.129)), and based on the observed network one might presume that most of these opportunities involved ending existing relationships as opposed to adding new ones. Students had about 1.3 opportunities to make changes to their technology use, with equal numbers increasing or decreasing their use by one level of intensity. Most students in the study maintained their Non-use level, which suggests that the students who did change might have increased by more than one level of intensity use between the first and final exams.

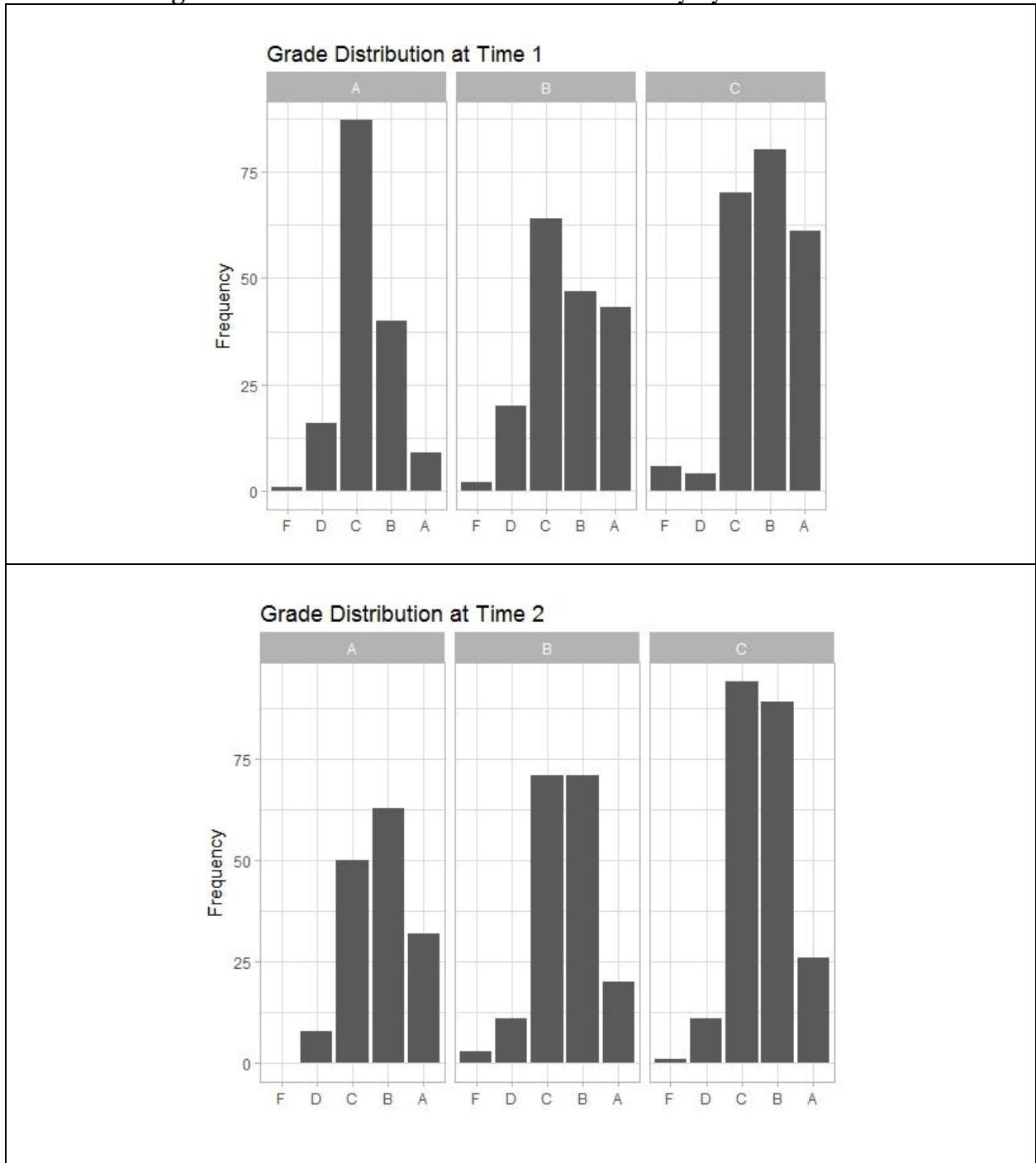
Appendix L. Course-work spans socio-material interactions and course space(s)

Table 37. Observation of Socio-Material Academic Engagement by Class Section.

Interaction	Location		Required?
	In-class	Out-of-class	
Socio-academic interactions	Attendance		Required
	Listening and note-taking	Study Groups Supplemental Instruction	Optional
Socio-material interactions	Practice Problems		Required
Material interactions	Exams	Practice Problem Website Use Online Homework system Class B: Pre-Lecture Videos Class B: Pre-Lecture Clicker Questions Class A: Python programming exercises	Required
		Reading and reviewing textbook Class A: Pre-Lecture Videos	Optional

Appendix M. Grade Distribution Figures

Figure 17. Grade Distribution before each survey by lecture section.



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