2016

A Social Network Analysis of an Introductory Calculus-based Physics Class with Comparisons of Traditional and Non-Traditional Students, FCI Scores, and Network Centralities

Emily Sandt
Wright State University

A SOCIAL NETWORK ANALYSIS OF AN INTRODUCTORY CALCULUS-BASED PHYSICS CLASS WITH COMPARISONS OF TRADITIONAL AND NON-TRADITIONAL STUDENTS, FCI SCORES, AND NETWORK CENTRALITIES

A thesis submitted in partial fulfillment of the
requirements for the degree of
Master of Science

By

EMILY SANDT
B.S., B.S. Ed., Bloomsburg University of Pennsylvania, 2014

2016
Wright State University

WRIGHT STATE UNIVERSITY

GRADUATE SCHOOL

June 22, 2016

I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Emily N. Sandt ENTITLED A Social Network Analysis of an Introductory Calculus-Based Physics Class with Comparisons of Traditional and Non-Traditional Students, FCI Scores, and Network Centralities BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science.

Adrienne Traxler, Ph.D.
Thesis Director

Doug Petkie, Ph.D.
Chair, Department of Physics

Committee on
Final Examination

Adrienne Traxler, Ph.D.

Doug Petkie, Ph.D.

Jason Deibel, Ph.D.

Eric Rowley, Ph.D.

Robert E. W. Fyffe, Ph.D.
Vice President for Research and
Dean of the Graduate School

ABSTRACT

Sandt, Emily Nicole. M.S. Department of Physics, Wright State University, 2016. A Social Network Analysis of an Introductory Calculus-Based Physics Class with Comparisons of Traditional and Non-Traditional Students, FCI Scores, and Network Centralities.

The use of social network analysis in physics education research seeks to advance understanding of how students' collaborative tendencies influence trends of learning. Common useful measurements are network size, density of connections, and centrality measures that describe the importance of nodes' positions. This study compared four different centrality measures at the beginning and end of seven sections of an introductory calculus-based physics course. The Force Concept Inventory was used as a measure of conceptual learning at pre- and post-course administrations. The main focus of this study was to identify if differences in network centralities and conceptual learning/knowledge exist with respect to students' designations as non-traditional or traditional (age 22+). Various class sizes, styles, and instructors were included in the data. Results showed some common and conflicting trends for the different class types, with non-traditional students generally at a disadvantage in network position but comparable in conceptual scores.

Contents

List of Figures

List of Tables

Acknowledgments

I would like to thank the Graduate Council at Wright State University for selecting me as a recipient of a Wright Fellowship award for the 2014-2015 school year.

Chapter 1

Introduction

The current state of post-secondary education, in particular, transitioning from traditional lecture-style teaching to that of active-learning and peer cooperation methodologies, has initiated large amounts of research. The majority of that research focuses on the effectiveness of each style and curricula and how successful these methods are when implemented in different classrooms. Cooperative learning has proven to promote better cognitive understanding of a subject while also enhancing students' abilities to think critically and problem solve, both integral features in physics [13] [17]. Logical questions can follow this conclusion regarding how well peer cooperation promotes meaningful learning: does this meaningful learning take place for everyone and how does the classroom environment affect the amount of learning?

This study focuses on the first of those questions: do all students (student groups) feel the same benefits from working with peers? The university at which this data was collected has a large amount of non-traditional (older) students [40]. These students face additional challenges in college as they are likely to have families, full-time jobs, and additional obligations limiting their time. Non-traditional students also are at different stages in their lives and may struggle to make on-campus connections with peers who have just graduated from high school. With this rare demographic distribution available, the groups chosen for comparison were traditional students, those likely attending post-secondary schooling immediately following the conclusion of their secondary education, and non-traditional students, who may be returning to post-secondary schooling to obtain a degree after working, serving in the military, etc.

The research focused on various sections of a first semester calculus-based introductory physics course. The classes were taught by several instructors over the course of a year and a half in a variety of classrooms using different instructional methodologies. As a measure of the amount of learning that occurred, a pre-course and post-course conceptual diagnostic exam was given to (almost) all sections. Using the pre- and post-course scores, a "gain" in conceptual understanding was determined. For the peer cooperation portion of data collection, a survey was given asking students to name peers in the class with whom they have worked in order to learn physics. The survey was also given pre- and post-course. The naming process allows a study network of the class to be generated. Social Network Analysis (SNA) techniques were used to quantify how much peer cooperation each student did throughout the course using measurements of centrality (the position of a student in the network). Several definitions of centrality were analyzed and compared with each measurement using a different definition of what it means to be a "central" figure in the network.

Since having more study partners would make a student more central, meaning more peer cooperation, previous research would imply that more conceptual learning would take place for those with higher centrality. In other words, having more classmates to be social with may help students be more engaged in the class and learn more. This additional learning could be reflected in conceptual gains. This idea has been supported by several physics education researchers [8] [9]. The inclusion of students being grouped by their traditional/non-traditional status is fairly unique in this setting.

1.1 Purpose of Study

The consideration of non-traditional students within a peer cooperation learning setting has not been fully analyzed. The objective of this study is to fill this void by comparing results between non-traditional and traditional students' centrality values and their conceptual gains. Particularly at this university, results from this study may be useful in the development of further support systems for non-traditional students, increasing the portion that finish their post-secondary educations.

1.2 Significance of Study

Analyzing non-traditional and traditional students separately allows investigations regarding how each student group networks within a classroom. Including conceptual gains in this analysis permits additional conclusions to be drawn regarding how strongly centrality can be linked to those conceptual gains for each student group. Definitive results may lead to differentiating instruction in a way that is more supportive to one group, particularly non-traditional students, for whom little research has been done with regard to their classroom networking. As education makes the shift to more cooperative learning environments from traditionally structured lectures, this data may prove to be very powerful in the fine-tuning of this fundamental educational transition.

This study is has a particularly high potential for meaningfulness as it includes data based on the individual student (their score on the conceptual exam) and the whole class (their centrality values within the network), creating a rather comprehensive look at the classroom and individual dynamics.

Previous research comparing traditional and non-traditional students has found that non-traditional students have lower rates of retention [35]. Other research suggests that attrition rates can be improved by creating the feeling of belonging to a community and having both academic and social support inside the classroom [39]. Deductive reasoning leads to the supposition that peer cooperation inside a classroom may lead to higher rates of retention among non-traditional students. If students learn more while working with peers while they simultaneous create a social study network by cooperating with said peers, they will have constructed a network of academic and social support that research suggests will lead to higher understanding of the subject being studied (and higher course grades). If a non-traditional student feels the presence of these support networks, is successfully learning in the class, and feels that they are indeed a member of the classroom community, they are less likely to drop out of their post-secondary program [39].

Chapter 2

Literature Review

Education as a whole is undergoing a profound transition from traditional lecture-style education settings to settings focused on hands-on, cooperative, and active learning. Studies have shown that students have better learning outcomes when these non-traditional learning styles are utilized in the classroom [23] [21] [17]. Increased success in classes leads to higher rates of retention within a student's post-secondary academic career. Previous research has identified non-traditional students, typically defined as over the age of 22, as having lower rates of retention [18]. Connecting these ideas, the question of the effect of the new teaching settings on non-traditional students comes to light. Do these students get the same benefit from cooperative learning in the classroom? Do they partake in cooperative learning at the same level as traditional students? For the purposes of this study, the amount of learning was measured by the Force Concept Inventory (FCI). The amount of cooperation was quantified using social network analysis (SNA) using a variety of network centrality measurements based on self-reported study partners.

Most of Physics Education Research (PER) has focused on individual measures and traits of students [6]. For example: does gender affect a student's score on an exam? Does a new curriculum produce satisfactory gains for students? Is there a particular characteristic in a group of students that may predict their ability to master some physics concept? Using network measurement methods from sociology and mathematics allows

PER to expand its viewpoint to include class dynamics. With full class analysis, PER is able to analyze how a student changes his/her position within the class network, as well as individual conceptual understanding changes. Combining these two different data types is a comprehensive way to analyze students within a class.

2.1 Force Concept Inventory

The Force Concept Inventory (FCI) is a 30-item multiple choice standard measure of students' conceptual understanding of how forces interact [25]. Hestenes and collaborators developed this diagnostic exam to force secondary and post-secondary introductory physics students to choose between their understanding of mechanical physics concepts and common sense alternatives [25]. Scores are based solely on the number of correct answers. No points were deducted for an incorrect selection, meaning there was no penalty for students guessing. The FCI is purposefully based on common misconceptions that students have about forces and mechanics. Due to this, it is especially resistant to students repeating "learned" material by memorization, as frequently done on exams, but requires a true understanding of force concepts. Comparing pre- and post-course FCI scores is a common way to see if, and by how much, students learned throughout the course. Typically the post-course scores are higher than the pre-course scores, which accompanies logic, since now students have taken a physics class [25] [21]. Additionally, a comprehensive study was completed to compare how interactive engagement educational techniques affect the amount of gain in conceptual knowledge using FCI score as the parameter [21]. With a sample size of 6,542 throughout a variety of classroom levels and structures (including secondary and post-secondary), all classes display gains in score, but there is an evident cap on the amount of gain in a traditional lecture style classroom. Engagement techniques eliminate that cap, but have a wider range of average gains [21]. This study is comprised of data using both types of classroom styles, thus comparisons between two types of classrooms may yield different results.

Huffman and Heller clarify that the FCI is a valid diagnostic for testing students' knowledge of force concepts after they criticized other aspects the diagnostic [26]. The criticisms included the vagueness of a question testing a student's conceptual understand or familiarity with the question's context and the basis that the FCI actually measures a "force concept." The pair used a factor analysis technique to determine that the question categories were not accurately assigned and that "...questions on the FCI are only loosely related to each other and do not necessarily measure a single force concept or the six conceptual dimensions of the force concept as originally proposed by its authors."The study uses only one version of the FCI, thus students are retaking the same exam as a post-test. Henderson verifies that this re-test is not a concern for creating a bias in scores [24]. Students do not know that they will be taking the same exam at the time of initial testing, so it is not likely that students would memorize answers. Since the exam is given fifteen weeks apart, it is also not likely that they would remember any of the questions [24].

2.2 Network Basics

Social Network Analysis (SNA) is a growing topic in the realm of PER. By studying the way a student networks socially in the classroom, the aim is to be able to predict the way a student will perform in the course. Networks, in this study, are created by designating each student as a vertex, or *node* [28]. Students then answer a check-box style survey in which they name other students in the class as study partners. Students may choose as few or as many peers as appropriate. This method of data collection (providing a class roster, rather than making students rely on their memory) is described by Marsden as one that reduces error in the data and allows for a comprehensive network [29]. This naming process generates a list of connections, or an *edge list* [28]. The *edges* (connections) are then attached to the node/student list to create a network of study partners within the class.

Networks can be directed, meaning that if Student A identifies Student B as a study partner, it is not assumed that Student B also identifies Student A as a study partner [32]. Visually the edge between the two nodes would have an arrow head point from Student A to Student B, but no arrow from Student B to Student A. Networks can also be weighted.

A weighted network identifies how many times or how strongly an edge is identified [32]. For example, if Student A was asked to rank Students B, C and D by how often they study together, Student B might get a value of 3 because they study together most. Student C might get a 2 for sometimes studying together and Student D might get a weight of 1 because Student A only studied with Student D on a rare occasion. Visually the edges would become thicker with a higher weight. Unweighted networks simply consider each edge to have the same value as any other edge, regardless of how strong the connection is.

This creates a large amount of data for a large lecture course. For ease of calculation, the data is stored in an adjacency matrix. Each "1" entry in the matrix represents a node, i, which has an edge connecting it to some other node, j, within the network [32]. For example, if students A, B, C, D and E are in the class and student A names student C as a connection, the adjacency matrix will show a "1" under row A, column C and row C column A. (Note: this is an undirected and unweighted network.) Additionally, self-identifications are not permitted as they are illogical. A student identifying themselves as a study partner provides no valuable data. An example adjacency matrix is below with a description of what the adjacency matrix represents:

$$R_{ij} = \begin{pmatrix} 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 \end{pmatrix} \tag{2.1}$$

R_{ij} should always be symmetric in an undirected network and should have zeros on the diagonal, as self-edges are not permitted. Even if C also named A (meaning the connection between A and C has been reported twice), the nodes are still connected by one edge with an entry of "1" in the adjacency matrix, as described above because this is an unweighted network.

A directed network R_{ij} will almost never be symmetric. Directed networks note which node named another node and store that data appropriately within the adjacency matrix. For instance, if A named C in a directed network, the adjacency matrix would have an entry in row A, column C, but not in row C, column A. Undirected and unweighted networks will *always* produce a symmetric matrix.

From the above adjacency matrix, a network diagram can be generated. This diagram is unweighted and undirected.

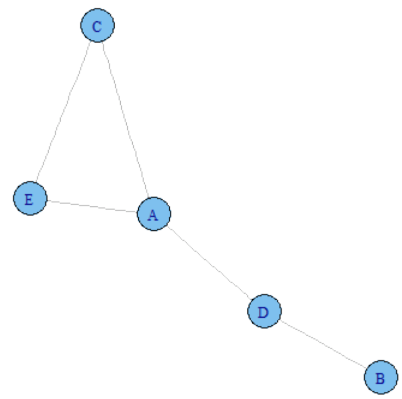


Figure 2.1: Sample Network: Here A, B, ..., E represent students, or *nodes*. The lines connecting various nodes are called *edges* and represent pairs of study partners. The network diagram is unweighted and undirected.

2.3 Centrality Measures

The objective of using network analysis is to be able to describe network dynamics over time and describe nodes based on their position and/or importance. Centrality measures provide a numerical value to the nodes' positions and allow for quantitative analysis and comparisons of the nodes' positions and importance. In the sample network shown in Figure 2.1, node A appears to be the most central, or important, node. Centrality measures provide a way to formalize this thinking and allow a quantitative analysis to take place. Nodes that are of higher centrality possess greater power within the network [12] [7]. There are several forms of centrality, each with its own definition of what "central" means and resulting implications of what processes are important within the network. The centrality measures of interest to this study are: degree, betweenness, closeness and PageRank.

2.3.1 Degree Centrality

Degree centrality is the simplest to calculate and conceptually understand of the centrality measures listed. Degree asks "how many people do you work with in the class?" This number has a minimum of zero if a student does not work with any peers and a maximum of one less than the total number of students in the class (as self-indications of study partners are removed due to lack of value). Degree centrality is important as working with more partners can lead to greater conceptual understanding of studied material [4]. For the network in Figure 2.1 node A has the highest degree with a value of 3. Node B has the lowest degree value with a degree of 1.

2.3.2 Betweenness Centrality

Betweenness centrality provides a numerical representation of how "between" other nodes a node is. Conceptually if a node has a high betweenness value, the node is likely a courier of information, such as force concepts, from one part of the network to the other. This is important because having high betweenness means that the node has a large amount of information passed through it. The more information and interaction, the higher the conceptual understanding the node should have if this position of "brokerage" (meaning middleman who passes conceptual information/knowledge) provides influence [16].

For the sample network, C and E share similar betweenness values as they are both on equally long (meaning having the same number of edges to cross) paths to connect to all other nodes in the network. Even though these nodes appear connected, they have betweenness values of zero; technically C is "between" A and E and E is between A and C. However, more direct (and thus, shorter) connection exists between each of those pairs, so the connection from C to E to A or E to C to A cannot be the *geodesic*, or shortest path between the two nodes. B has no betweenness centrality as there is only one edge for that node so it cannot be "between" any pair of other nodes. Node A has the highest amount of betweenness as there is only one pair of nodes that can communicate without involving A. D has a moderate amount.

2.3.3 Closeness Centrality

Closeness describes almost a physically measurable parameter of a node within a network. Closeness calculates the inverted sum of the paths from the node of interest to all other nodes using the between the two [16] [12]. Nodes that are "close" receive information faster and more frequently than a node that is on the outskirts of a network. Additionally, closer nodes likely receive more factually correct information as the information has not passed through much of the network to get very distorted.

For the sample network above, A has the highest closeness centrality, and B has the lowest. C and E will have moderate values as they are "close" to nodes A and D.

2.3.4 PageRank Centrality

PageRank is a parametric model of centrality, unlike the previously discussed empirical models [37]. (This means that one node is given an initial value of PageRank centrality, and all other nodes get values based on the first value-so node A's PageRank is based on node D's PageRank and so on.) PageRank analyzes connections of the nodes which are connected to the node of interest. If the node is connected to other nodes that have a high number of edges, the node will have a high PageRank [34]. This technique has been applied to airport and internet models and ultimately was the birth of Google [34] [37]. This centrality method provides valuable information as it describes the characteristics of a node's connections, and thus incorporates information about its neighbors' importance in addition to itself.

For example, in the sample network above, D does not have a high degree centrality and has moderate betweenness and low closeness centrality values, but has a fairly high PageRank as D is connected to A and A is connected to most other nodes in the network.

2.3.5 Figure 2.1's Centrality Values

The table below lists the various centrality measurements for each node in Figure 2.1.

Centrality Type	Node A	Node B	Node C	Node D	Node E
Degree	3	1	2	2	2
Betweenness	4	0	0	3	0
Closeness	.200	.111	.143	.167	.143
PageRank	.283	.120	.192	.213	.192

Table 2.1: Figure 2.1 Sample Network Centralities.

2.4 Previous PER with Network Analysis

PER has been expanding its research base in recent years to include network analysis techniques frequently used in sociology and mathematics research. Rather than focusing on individual student data, network analysis allows researchers to study the class dynamics as a whole in any discipline [20]. Combining these two data types is an innovative technique to obtain more comprehensive research results. Analyzing network structure provides researchers with a method to determine how students group together and build small communities [15]. Receiving instruction in different classroom settings influences how students will network in the classroom. For example, an auditorium-style seating classroom with traditional lecture format does not allow much peer interaction in class, however cooperative group problem-solving environment enables students to make those connections within the confines of the classroom walls. Dawson concludes that identifying students' positions within the network can allow ties to be made to their sense of community and support in both academic and social arenas [15].

Additional research has yielded results to support more integrated instructional methods. Brewe compared results from a Modeling Instruction (MI) and traditional lecture format of the same course [8]. The MI class used interactive engagement methods and encouraged student teamwork and problem solving. Social network data was taken at pre- and post-course and revealed little to no change in the lecture format section but dynamic change in the MI class [8]. Students in the MI section made significantly more connections with peers to the point that there were no isolated students. The increase in connectedness based on the instructional technique provides an important connection between the effect of classroom environment and instructional methods and students' interactions.

Connecting the interactions to meaningful learning characteristics is the next step in this type of research. Common SNA measures to study are those of centrality. Common PER measures to study are FCI scores. Combining these two common data types has been the basis of several PER studies. Bruun and Brewe researched the ability to predict future grades using FCI pre-course scores and centrality measurements [10]. The pair analyzed survey data taken each week regarding study partners and created a complex network. Several centrality measures, including degree, were calculated. Correlations were made between centrality values, pre-course FCI scores and students' grades received in later physics classes to find relationships between grades and network centrality measures. The authors suggest that the results imply social interactions are integral to learning [10].

There is a drive for SNA to be implemented in other types of PER as well. A case study approach was completed at the same university as Brewe [19]. The Modeling Instruction classroom was again used and three students' interviews were reported. Measures focused on attitudes about learning, ties within the classroom, and relationships within the physics learning community. An attitudinal survey was given to obtain the first of these measures, SNA provided the second dataset, and interviews provided the final aspect. Two of the three students showed very high gains in centrality and reported feeling as though they were an important part of the learning community within the classroom [19]. Both had increases in positive attitudes about physics and their learning environment. The third student did make more connections, but not as many as the others. The student has a place in the class network but is toward the sideline rather than midfield. No attitudinal shifts were reported but the student entered with an appreciation for learning physics in a cooperative setting [19]. The study suggests that obtaining a more central position in the network may lead to feelings of inclusion and importance in the learning community. From previous research, community inclusion can lead to increased successes in courses [10].

2.5 Non-Traditional Student Status

As with many education studies, the overall objective is to identify strategies and techniques to further aid in students' learning. One way this can be done is to encourage students to stay in school and increase the rates of retention. Tinto identifies the feeling of inclusion in social and academic forums leading to increased learning and student effort and retention [39]. Tinto saw a void in student persistence research linked to in-the-classroom interaction and student involvement [39]. Focusing on that void, he looked at social and academic interactions within the classroom, positing that may be the only time non-traditional students get this interaction. Increasing in-class interactions such as these, yields a community-like environment where students feel included and are likely to continue with their studies [39]. This is supported by Gilardi and collaborator's study on engagement styles and attrition rates [18]. Gilardi and Guglielmetti analyzed various definitions of non-traditional students and surveyed their opinions on their university experiences during their first year as students. The university experience includes class attendance rates, initiating contact with professors and peers, social integration perceptions, meaningfulness of the learning, and intensity of difficulty perceptions. The study revealed that non-traditional students require a greater use of learning support opportunities (such as study groups and tutoring sessions) and higher levels of social integration [18].

It stands to reason that students who are successful in their studies are more likely to continue their academic careers until they are fulfilled and will not drop out of a post-secondary degree-seeking environment. Retention is a concern particularly for older students [18]. There are several characteristics that a typical non-traditional student may have, such as: a full-time job or multiple part time jobs to support themselves, a spouse and/or child(ren), and additional responsibilities, perhaps caring for an aging relative. One characteristic that most non-traditional students share is being older than the average college student. There are various definitions for what defines a non-traditional student which can contain one or all of the above listed factors. Wright State University defines a non-traditional student as one over the age of 22 and will thus be the definitive factor for this separation in this study [40]. Wright State University has a high population of non-traditional students at one-third of the undergraduate student population being 23 years of age or older [40]. This student body provides a rare opportunity to study the differences between traditional and non-traditional students.

At the same time, the physics department is undergoing a transition from traditional lecture-style classrooms to SCALE-UP and flipped classrooms. Classrooms are structured differently in both teaching methods and physical arrangement. SCALE-UP and flipped classrooms provide more student engagement through group problem solving and peer-cooperation [5]. Rather than an auditorium style of seating, SCALE-UP classrooms provide small tables with seating from 3-9 and laptops for each student or 3-person group [5]. This study contains a variety of classroom structures and sizes in which non-traditional student centrality and conceptual learning trends can be compared to traditional student values as well as across the classes.

Chapter 3

Methods

3.1 Introduction

The introductory calculus-based physics course has three components: a lecture, meeting approximately 3 hours per week, a recitation section, meeting 1 hour per week or built into the course, and a laboratory section, meeting 2 hours per week. While the lab instructors varied, the materials, experiments, and structure were identical. Lecture styles and frequency varied between sections. Each course had one (unless otherwise noted) graduate teaching assistant to aid the professor. The two tools for data collection were the FCI and an online survey, which collected network data. Both were administered during the first and last weeks of the semester.

3.2 Participants

Wright State University houses six colleges and three schools. WSU has over 18,000 students and offers over 100 undergraduate and 40 graduate/professional degrees. The university has a high number of non-traditional students (defined by an age greater than 22 years): over fifty percent [2]. WSU is largely a commuter school with under fifteen percent of students living in on-campus housing [2].

The majority of the participants in this study were engineering majors who were taking the course to fulfill a major requirement. The course required students to have passed Calculus I or an engineering calculus substitute course.

3.3 Data Collection

3.3.1 Instrumentation

Both the Force Concept Inventory (FCI) and the online network survey were administered during the first and last week of the course. The pre-course FCI was given during the first week of class, either in the lecture portion of class (datasets A, C, F and G) or during the first lab meeting (datasets D and E). The post-course FCI was given in class during the last week of classes for the semester. Students were given 35 minutes to complete the exam and fill in their answers on a Scantron form. In most sections, students received extra credit for completing the exam; in all but two sections, this credit was for participation rather than correctness of answers. Students were not told that it was the FCI (rather it was titled a "Diagnostic Exam"), to avoid the possibility of students searching for answers later. The Scantron forms were scanned and answers were returned in the form of a spreadsheet.

A hyperlink to an online survey was provided to students to be taken on their own time. All classes (except dataset D) gave the students extra credit if they completed the survey. Survey participation, or lack thereof, never negatively affected a student's grade. The survey provided students with a roster of the students in their section of the class and asked them to check the boxes next to the names of those students that they "study with to learn physics." (Directly from the survey in Appendix D: "Who do you study with to learn physics?") This style of surveying students is supported by Marsden [29] and allows students to pick as many study partners as are applicable but does not force students to remember their names. This network data was returned in the form of an adjacency matrix (described in Section 2.2) spreadsheet. Possible missing data can be introduced here as a student may be named by peers, but did not fill out the survey him/herself. When identified as a study partner, that student obtains a degree value, whether he/she completed the survey or not. Who provided the data is not identified differently in this study, since the network used is undirected and unweighted.

Demographic information (student ages) was provided by Institutional Research at the university. Not only is approval from the Institutional Review Board required, but Antonellis et. al [3], argue that in education research it is especially important to make sure the students are treated appropriately. A cover sheet informed students of what the survey was aiming to gather, what the data would be used for, and its confidentiality status and asked for consent (see Appendix C).

3.3.2 Section Details

Dataset A's class was taught in a large auditorium-style lecture hall (seating up to 300) and met 3 times each week for 55 minutes using lecture and some in-class peer instruction [31]. The instructor's station housed an interactive computer and document camera which linked to a backlit screen above the chalkboard for student viewing. Recitation was held separately in smaller sections (<40 students per recitation) and used cooperative group problem solving [22] [23] as its primary instructional technique. Two graduate teaching assistants (GTAs) worked with this class.

Dataset B was taught in a similar room to dataset A's class. The class was solely lecture-based and met twice a week in the evening (considered a night class) for an hour and 20 minutes. Recitation was held separately in smaller sections, similar to dataset A's class.

Dataset C's class was taught in a 36-person SCALE-UP classroom with computers at each of the 6 seats at each of the 6 oval tables. Television screens were at the ends of each table which students could link to or the professor could control. Projectors and whiteboards lined the walls. The instructor's station housed a computer with the ability to enable/disable student computers, display content on all (or certain) screens, and make on-screen annotations. The class met for an hour and forty minutes, three times per week with no additional recitation. This section used many of the same instructional techniques as dataset A, but had more peer instruction and group problem solving.

Dataset D was taught in another large auditorium-style lecture hall with seating for roughly 200 students. The instructor station was similar to that of dataset A's classroom except the projector's screen was not backlit. The instructor did not use any peer instruction methods in the lecture, which met 3 times a week for 55 minutes each time. A 1-hour recitation was held separately and did encourage some group problem-solving depending on the recitation instructor. No teaching assistants were used in this class.

Dataset E was a larger version of dataset C's class. This SCALE-UP room had 6-person round tables and could hold 108 students. The instructor station had identical capabilities as that of dataset C's. Students were grouped together in groups of 3 and two groups sat at each table. Two graduate teaching assistants and 2 undergraduate learning assistants (LAs) were involved with this course. The class had built-in recitation and met 3 times a week for an hour and twenty minutes at a time.

The F and G datasets were taught in a small classroom with seating for 30. The room had tables grouped together with 4-6 seats at each table. A projector and whiteboard were available for use. The instructor did not use peer-instruction but did use cooperative problem-solving techniques. Recitation was built into the classtime, which met twice a week for an hour and fifty minutes. F was an early morning class and G was held mid-morning.

Table 3.1 summarizes the above descriptions of the individual datasets.

Dataset	Class Type	Recitation	Interactive Group Problem Solving	Lecture Class Size	Other Notes
A	Lecture	Separate with Group problem solving	Both with peer instruction	200	50% international enrollment 2 GTAs
B	Lecture	Separate	None	190	-
C	SCALE-UP	Built into lecture	Both with peer instruction	30	more interactive than A and 1 GTA
D	Lecture	Separate	None	110	-
E	SCALE-UP	Built into lecture	Both with peer instruction	70	2 GTAs and 2 LAs
F	Lecture	Built into lecture	Cooperative problem solving	20	1 GTA
G	Lecture	Built into lecture	Cooperative problem solving	30	1 GTA

Table 3.1: Summary of dataset details.

3.4 Data Analysis

3.4.1 Data Cleaning, Matching and Importing FCI Data

Using Microsoft Excel, the FCI pre- and post-course data were graded and given scores based on correctness out of 30. Each question answered correctly earned the student one point. No points were deducted for incorrect answers. The student name, university identification number (UID) and score were transferred to another file where pre- and post-scores were matched. (Some students did not take the FCI at both points of the course, so pre-course scores existed, but there was no post-course score, and vice versa.) If pre- and post-course scores were present, the "gain" was calculated by subtracting the pre-course score from the post-course score. Using raw (unnormalized gain) was chosen in an attempt to avoid low score bias, discontinuities if the pre-course score is 30 and issues with decreases in score, as discussed by Max and Cummings [30]. This file was then imported into the open-sourceware program, *RStudio* [38], which is a user-friendly interface of *R* [36].

3.4.2 Data Cleaning, Matching and Importing Network Data

The online survey returned an adjacency matrix in spreadsheet form. It was cleaned and processed (mainly removing duplicates and correcting incorrect capitalization) and imported into *RStudio*. The data was further manipulated to create a list of named individuals (nodes) and named links (edges) using the *reshape* package [41]. Using an *RStudio* package, called *igraph* [14], a network object was generated which contained all of the named study partners as well as all of the identified connections. Igraph plotted the networks and they were made undirected.

FCI scores and demographic information (age) about the students were matched (where available) to each student using their UIDs.

Generating Network Diagrams

Igraph was primarily responsible for creating intricate network diagrams and manipulating the nodes by size, shape, and color based on the data. The network objects were created to display multiple data points for each node. This data was attached to the node entry and used in the plot to vary color, size, or node shape. Interesting data for the purpose of this study was: students' ages; students' connections to each other; and pre-course, post-course, and gain in FCI scores. Using ages (reported from the Institutional Review office) as guidelines, students were categorized as traditional (22 or younger) or non-traditional (over 22). Network diagrams display the network structure, allow central nodes to be visually identified easily and can display additional data via node color, size, and shape by writing functions and using the *RColorBrewer* palette [33].

3.5 Various Centrality Measures

When looking at a network, certain nodes can be identified as being well-connected and others may not be connected at all. The amount of connected-ness of a node is also called *centrality*. If a node is very well connected within a network, that student would have a high centrality, hopefully leading to high performance in the course. By working with more peers to learn physics, students are expected to have additional resources for learning which should improve their knowledge. There are various measures centrality for a node's place within the network, each reflecting a different model of which processes are the most important. Some interesting network centrality measures are: degree, betweenness, closeness, and eigenvalue centrality. Each measure produces slightly different results and gives a numerical representation for a different aspect of the network's shape. The formulas used for each centrality measure are provided and explained below. All explanations and formulas are representative of an **unweighted** and **undirected** network. Note: *igraph* has these centrality calculations as pre-existing functions.

3.5.1 Degree

Degree centrality describes how many connections a node has out of the total number of connections a node could possibly have.

$$C_D(i) = \frac{\sum_{j=1}^{n} R_{ij}}{n-1}, \mathrm{i} \neq j \tag{3.1}$$

where i represents the node of interest and j represents a different node within the network [16]. If a connection between i and j exists, R_{ij} will be 1. A summation obtains the total number of connections from the i^{th} node to other nodes in the network. This is the normalized version of the formula, as shown by dividing the sum of connections by the total number of possible connections to the rest of the n nodes. Both normalized and unnormalized values are reported in Chapter 4. Normalized values make comparisons between other centrality types easier, but unnormalized values are conceptually easier to understand and discuss, and thus are used as the primary degree values.

3.5.2 Betweenness

Betweenness centrality describes how much a node is between other nodes. How would removing this node affect the flow within the network? This is determined by identifying the number of shortest paths (geodesics) from some node, j, to another node, k, in the network. If the current node of interest, i, is on the shortest path, $d_{jk}(i)$ obtains a value of 1 for each of the geodesics i is on. This is then divided by the total number of geodesics from j to k. A summation is completed for all j and k nodes in the network and that total is the betweenness centrality value for node i [16]. This formula is also normalized and all presented data will use the normalized form as well.

$$C_B(i) = \sum_{j<k}^{n} \frac{\frac{d_{jk}(i)}{d_{jk}}}{\frac{1}{2}(n-1)(n-2)} \tag{3.2}$$

3.5.3 Closeness

Describes how close the node is to other nodes within the network. How many paths does a bit of information need to take to get from this node to other nodes within the network? This is based on the length of the average shortest path between the vertex of interest, *i*, and all other nodes in the network, *j*. As represented here, the closeness centrality is normalized by dividing the sum by the number of non-*i* nodes within the network *(n-1)* [16]. Because this is an inverse relationship, some discontinuity occurs when node *i* is not connected to the central network object (so it would have a path of infinite length).

$$C_C(i) = \left[\frac{\sum_{j=1}^{n} d_{ij}}{n-1}\right]^{-1} \tag{3.3}$$

3.5.4 PageRank

PageRank centrality describes how well a node's connections are connected and how important they are [1]. Does the node associate with other nodes that have many connections? Do those connections connect with everyone? Unlike the previous centrality types, this one is inherently dependent on the PageRank centrality of its connections which requires solving a system of simultaneous equations for the whole network. This centrality measure uses eigenvalue and Katz centrality calculations as its basis [43]. Eigenvalue centrality solves the classic eigenvector problem and gives a constant for normalization of the solution vector, which holds the centrality values for each node. Katz centrality adjusted this model to give nodes who would have a eigenvalue centrality of zero some centrality value by adding a bias term (β) and altering the normalization constant [43]. PageRank has added a second normalization factor onto the Katz model that modifies the equation to account for how many connections node *j*'s connections make, N_j. Does being connected to node *j* make node *i* special? As shown below, the PageRank of node *i* is found by summing the PageRank of all nodes *j* connected to node *i* and dividing by the number of links from node *i*. c is a normalization value and C_k is the set of nodes that have edges connecting to node *i* [34]. There are two ways to have a high PageRank centrality: (1) be highly linked and (2) be linked to other nodes that do not link very often but are important. After using this centrality model, it is clear that the direction of identified connections matter. While calculations were done and are reported using an undirected network, it should be kept in mind that this model was not intended to be used on the undirected networks in this study.

$$C_{PR}(i) = c \sum_{j \epsilon C_k} \frac{C_{PR}(j)}{N_j} + \beta \tag{3.4}$$

3.6 Figure Generation

Visual analysis of a network diagram is not straight-forward and can be quite subjective. Different network pictures are drawn each time a network drawing is produced because the drawing algorithms are non-deterministic. Additionally, the pictures can appear skewed when several nodes are densely linked and are plotted close together, so they visually look central, but that "distance" is not a measure of their connectedness. For this reason, other plots were generated to what type of relationship exists between characteristics of the data. A popular plot to help in the understanding of a network diagram is a logarithmic-linear plot of the centrality values (especially for degree). This plot is called a cumulative degree (or other centrality) function plot and plots the degree (or other centrality) value on the x-axis with the proportion of nodes who have at least that value on the y-axis. As the x-axis values increase, the y-axis values decrease since less students will have higher centrality values. Log-linear plots show what the distribution of a network looks like. Additionally, the general distribution can be compared to the distribution of subsets of traditional/non-traditional students as described in Section 4.

A specialty diagram, called an alluvial diagram, shows the dynamics of a data set change over time [37]. Alluvial diagrams were generated using *plyr* [42] and various aspects of the data to display how it changed from pre- to post-course. This type of diagram allows the reader to see how each subset of data is distributed and transitions throughout the whole data set, especially from pre- to post-course.

Histograms and boxplots were created in order to display differences in FCI scores and gains for each subsetted student status.

3.7 Correlations and Statistical Tests

Several correlation methods were utilized for analysis due to the various nature of the data analyzed. *R* contains Pearson, Kendall, and Spearman correlation techniques. Significant correlations between a student's pre- or post-course degree and FCI pre- or post-course score or FCI gain were run using the Pearson permutation (*10,000 iterations*) technique, since the data is independent [20]. Correlation results from this test would indicate that a student's degree is directly linked to their performance on the FCI, hence their level of conceptual knowledge. Any results that returned a p value of $< .05$ had an effect size calculated [11].

The various centrality methods were correlated with each other using a permutation technique. Since the centrality measures have different assumptions about what is most important in the network, it is of interest to see if the different measures give the similar results (by returning a high correlation) or if they prioritize different nodes. Because the data is no longer independent, it is necessary to see how unique the ordering of the values are; this is done using a permutation test. (Orders of values were used to avoid issues with scaling between the different centrality measures.) Both Kendall and Spearman permutation correlation tests were used [27]. The tests resample the data to be tested according to the number of iterations desired (*1,000*) and compare the actual ordering to the reorderings. The percentage of the random re-orderings that return a result equal to or greater than the observed correlation coefficient represents a p-value. If the actual ordering does not happen by random chance, it is significant. Both tests returned p values of 0 (or practically 0) for tested correlations between the ordering of each centrality type. This does not mean that all nodes' centrality values were in the same order, only that their order is significant and not random. Table 2.1 confirms that ordering the nodes by centrality values does not mean all centrality values have the same order.

The final statistical test completed was the t-test. This was done on the subsetted data for like measurements (such as pre-course degree of traditional and non-traditional students). Results here are important as they specifically show differences in traditional and non-traditional students. If traditional students have significantly higher degree values at the post-course in a highly interactive classroom, we may conclude that non-traditional students did not network as effectively, for example. Any results with p-values < .05 had effect sizes calculated using Cohen's d which utilizes their mean values (m_a, m_b) and pooled standard deviation [11].

$$d = \frac{m_a - m_b}{\sigma_{pooled}} \tag{3.5}$$

Chapter 4

Results

Results are presented for each section separately. The first portion of each result set will list the response rates for the surveys. Then the results will focus on data and analysis for network information, followed by data and analysis for the FCI. The final section of results will combine both sets of collected data and look for correlations.

The first set of reported results is comprehensive, while subsequent sections have been trimmed to show only interesting figures and results or have been moved to Appendix A. Additional information on these datasets can be found in Appendix B.

4.1 Dataset A Results

This class took place in a large traditional lecture hall with seating for 300. The class met three times per week with a separate recitation section meeting once weekly. Each meeting session was 55 minutes long. The instructor utilized in-class peer cooperation instruction methods daily. Approximately half of the students were international which may affect results in both network and FCI data. International students may enter the course with a large network of peers from their home countries and face additional challenges with working with peers and language barriers may muddle FCI comprehension. Table 4.1 provides information about the class size and rate of responses for the collected data as well as the network density (the portion of the portion of edges in the network out of all possible edges).

		Pre-Course	Post-Course
Class Size		203	209
	FCI	0.94	0.73
Response Rate	Network Survey	0.95	0.63
	FCI and Network	0.88	0.64

Table 4.1: Response rates for the data collected are shown. While response rates for post-course appear low, these are comparable to all other sections of presented data. Note that for the combined surveys the reported rates were calculated using students for whom network and FCI data existed. This means a student who did not actually respond to the network survey, but was named in someone else's response and took the FCI will be counted in the rate.

4.1.1 Network Data

Table 4.2 provides values of the number of nodes and edges in the pre-course and post-course networks. From pre- to post-course node values decrease, but edge values increase. This is reflective of students making more connections throughout the course and supports the accompanying data of gaining connections over the course of the semester.

		Pre-Course	Post-Course
Number of	Nodes	203	174
	Edges	283	378
Network Density		0.014	0.025

Table 4.2: Number of nodes and edges (student identified connections) in A's data. Post-course has less nodes, as students have dropped the class, but more connections. The network density values also indicate a more connected network.

4.1.2 Network Diagrams and Statistics

Figure 4.1 provides a pictorial representation of the network structure of the class at the start of the course. Each node represents a student in the course who has either been identified as a study partner or has identified others as study partners. These relationships are denoted by edges (or links) on the network. The links are not weighted (so a pair of names identified once is the same thickness/value as a pair of names identified twice, etc.) or directed (student A naming student B looks the same as student B naming student A). Nodes are sized by their value of degree centrality. Degree centrality is defined as the number of connections a node makes. A larger-sized node indicates a higher number of connections. The nodes are also shaped according to their designation as a non-traditional (22+ years old) or traditional student. Some students did not have ages on file; they are given a separate shape (triangle). Lastly, the nodes are colored by their pre-course Force Concept Inventory scores. Darker hues indicate higher scores.

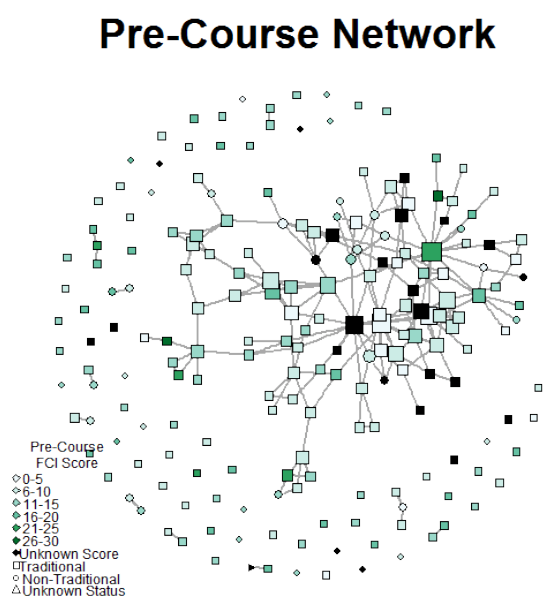


Figure 4.1: The pre-course network is colored by FCI pre-course scores, sized by post-course degree centrality value, and shaped by student non-traditional/traditional status. There are 203 nodes with pre-course FCI scores for 178 of them.

Figure 4.2 provides a pictorial representation of the network structure of the class at the end of the course. Nodes are colored by their gain in score on the FCI. Red hues indicate regression or a loss of correctly answered questions, while blue hues represent gains. Darker hues indicate greater change from pre- to post-FCI score. White nodes are students who had no change in score and black nodes represent students who did not take either the pre- or post-course FCI so there was enough data to calculate gain.

Nodes are shaped by their status as traditional or non-traditional students and sized by post-course degree centrality values.

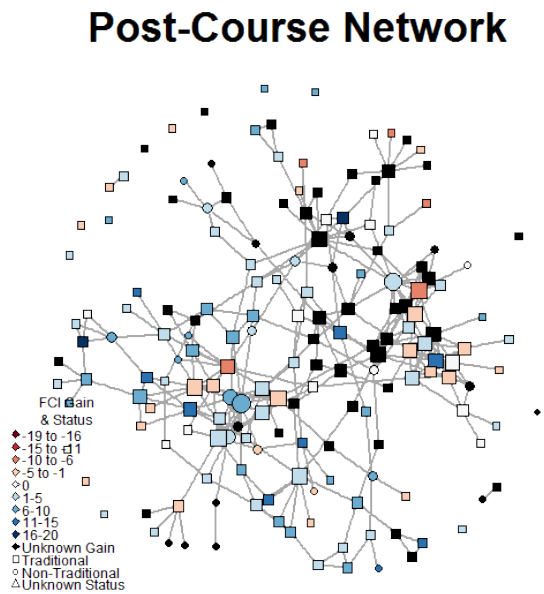
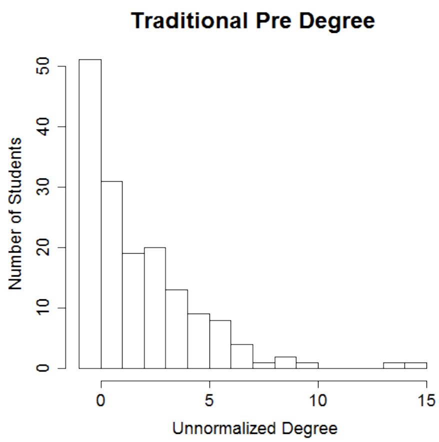


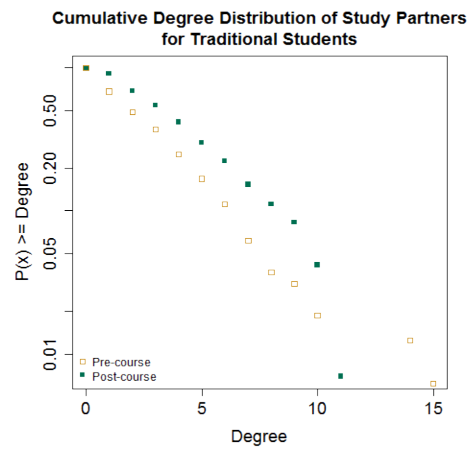
Figure 4.2: The post-course network is colored by FCI score gain values, sized by post-course degree centrality values, and shaped by student non-traditional/traditional status. There are 174 nodes with FCI gain values for 160 of them.

Log-Linear Plots

With the exception of closeness, all centrality measures analyzed show a logarithmic relationship with regard to frequency. In other words, most students tend to have a low centrality. As the centrality value is increased, the number of students who have a centrality at or above that value lessens in a logarithmic fashion. Histogram plots are a good visual of this relationship (see Figure 4.3a). When a logarithmic relationship is plotted on a logarithmic-linear graph, the result should be linear, indicating that the relationship is indeed logarithmic. An example of this is shown in Figure 4.3b. The linear relationship shows that as the centrality value is increased along the x-axis, fewer students are at or above that value. Each plot contains an initial point at a centrality value of 0 which will have a y-value of 1. This is logical as there are no negative centrality values so all nodes must have a centrality value equal to or exceeding 0. The 0 point is retained to more easily compare between different plots. (These plots are also called cumulative centrality function plots. For easier phrasing, CDF will represent cumulative degree function, CBF will stand for cumulative betweenness function, and CCF is the acronym for cumulative closeness function.)



(a) Pre-course degree histogram for traditional students. Degree values are on the x-axis and the number of nodes with that degree are plotted on the y-axis.



(b) Pre- and post-course degree values for traditional students plotted on x-axis with the logarithm of the proportion of students meeting or exceeding that degree on the y-axis.

Figure 4.3: A comparison of a histogram to a log-scaled frequency plot is shown. Note that while only the pre-course degree histogram is shown in Figure 4.3a, pre- and post-course values are plotted in Figure 4.3b.

Log-Linear Degree Plots Figure 4.4 presents the portion of students (out of 1, or 100 percent) who have a degree equal to or greater than some x (degree) value. Both the pre- and post-course relationships are shown. Outlined gold shapes represent pre-course data and solid green points represent post-course data. Square shaped data points represent traditional students, while circles shows the non-traditional students. The proportion of students with a lower degree is higher and continually drops as the degree value increases. The figure also shows that the fraction of students with a given degree value is lower for the pre-course than for the post-course. This result indicates that students gained study partners throughout the course.

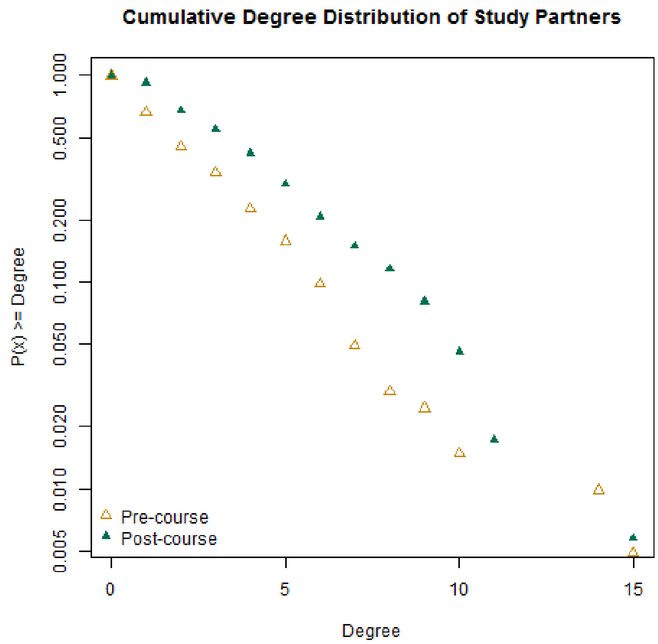


Figure 4.4: A logarithmic-linear cumulative degree distribution plot where *n=203* for the pre-course and *n=174* for the post-course plot. Shows a logarithmic relationship of students having a degree equal to or greater than the x-axis value.

In Figure 4.5 the proportion of students with a lower degree is higher and continually drops as the degree value increases. Overall, this plot shows a fairly steady relationship. Most students seem to gain only a couple more study partners. This could be due to already having a study network from pre-requisite courses. The shape is fairly comparable to Figure 4.4. Due to low *n* values, the tail (degree >10) of the plot contains noise. Three students are represented by the highest pre-course value and one student creates the maximum post-course value. When comparing Figure 4.6 to Figure 4.5, non-traditional students appear to gain more study partners than traditional students.

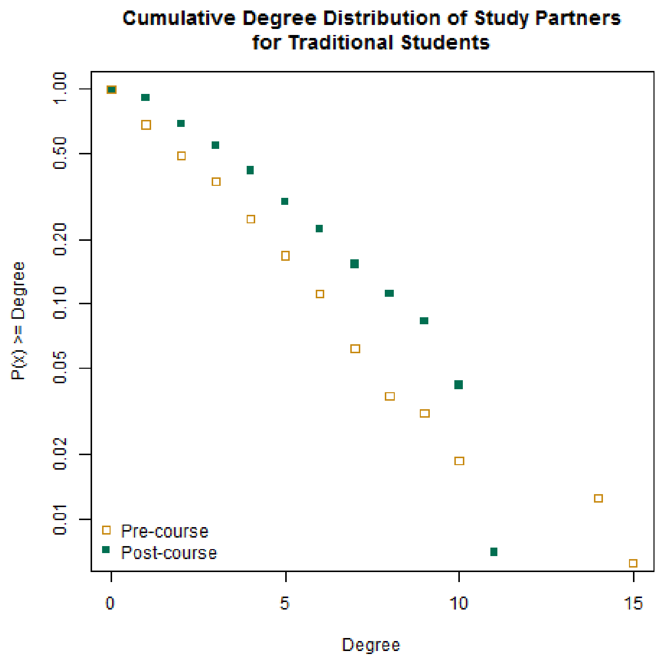


Figure 4.5: A cumulative logarithmic-linear plot of degree centrality for the subset of traditional students. Pre- (*n=161*) and post-course (*n=144*) plots are shown. Trends are consistent with those of the overall class shown in Figure 4.4.

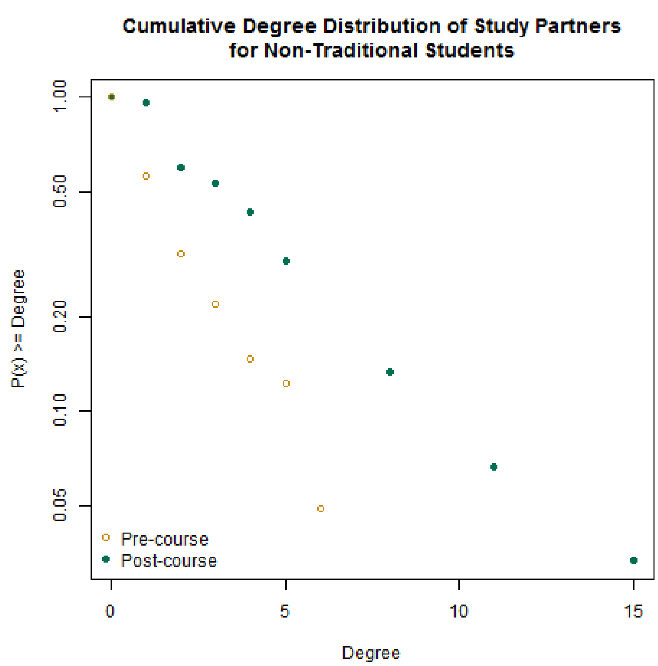


Figure 4.6: Non-traditional students' cumulative degree centrality values plotted with a logarithmic y-axis. Non-traditional students appear to have a larger gap from pre- (*n=41*) to post-course (*n=30*) indicating they gain more study partners throughout the course.

Figure 4.7 shows individual characteristics of traditional and non-traditional students' cumulative degree distribution at the pre- and post-course. Despite the lower initial values for non-traditional students, the post-course degree distribution of each subset is essentially the same. This means that, while non-traditional students tend to work with less peers at the beginning of the course, they make more connections throughout the course and end having a nearly identical amount of cooperating peers as traditional students. As in other degree plots, the highest degrees represent only a few data points and thus can be noisy. For example, the post-course traditional outlier at degree 11 is the result of one data point.

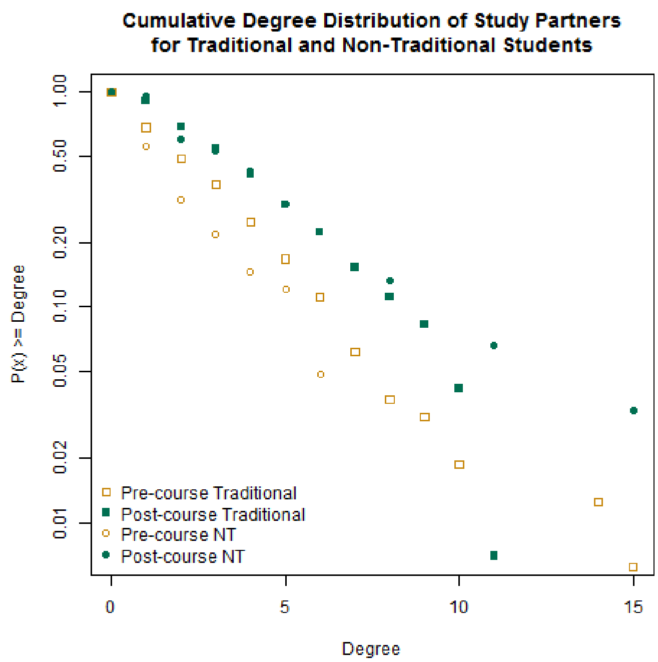


Figure 4.7: Figures 4.5 and 4.6 are superimposed to show that non-traditional students have a lower pre-course degree, but gain more study partners than traditional students. The two groups appear to have comparable numbers of study partners at the end of the course.

Log-Linear Betweenness Plots Figure 4.8 shows individual characteristics of traditional and non-traditional students' cumulative betweenness distribution at the pre- and post-course. The figure shows that the fraction of students with low betweennesss is lower for the pre-course and higher for the post-course. The plot shows a two-stage slope downward. For the pre-course, there are only 4 data points creating the secondary slope (*betweenness* > *.03*) and *n=15* for the post-course betweenness values greater than .05. Interestingly, non-traditional students seem to start with overall lower pre-course betweenness values, but have post-course values initially above those of traditional students. This indicates that non-traditional students must have some unique (probably finger-like) connections where they are the only study partner to some other student. With only one path for conceptual information to flow through, the student must be between its fingertip connection and the rest of the nodes in the network. Non-traditional students have a fairly constant downward slope with the exception of a small bump around betweenness values of .025. This is discussed below.

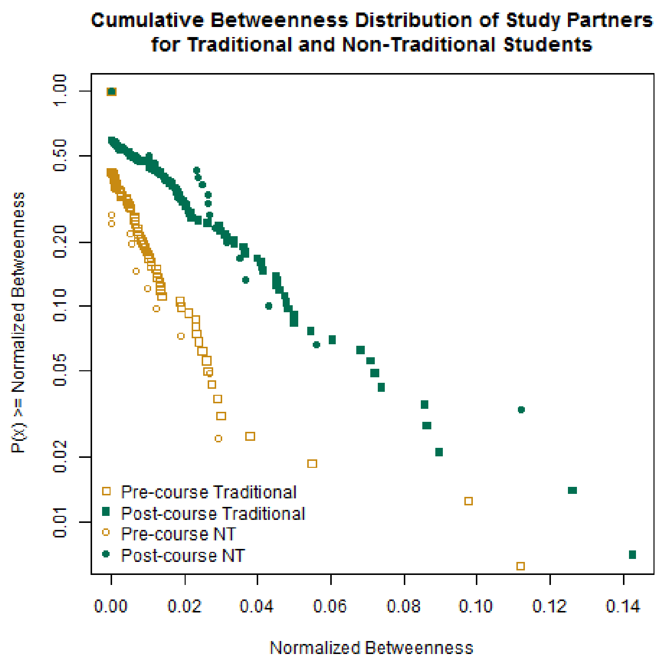


Figure 4.8: Non-traditional and traditional student subsets overlaid. Pre-course comparisons reveal that non-traditional students begin with lower betweenness values but seem to be comparable in the post-course. There are 4 data points in the pre-course traditional tail and 10 in the post-course tail.

The interesting "bump" in the non-traditional student plot in Figure 4.8 is intriguing. Figure 4.9 plots the post-course network and colors the nodes by those students contained within that bump. While the nodes are not concentrated in one particular place in the network diagram, a number of them appear to be the only connection from a few nodes to the rest of the class. This is similar to your hand structure: without your wrist, your finger(tip)s would not be connected to the rest of the network, therefore your wrists have betweenness centrality.

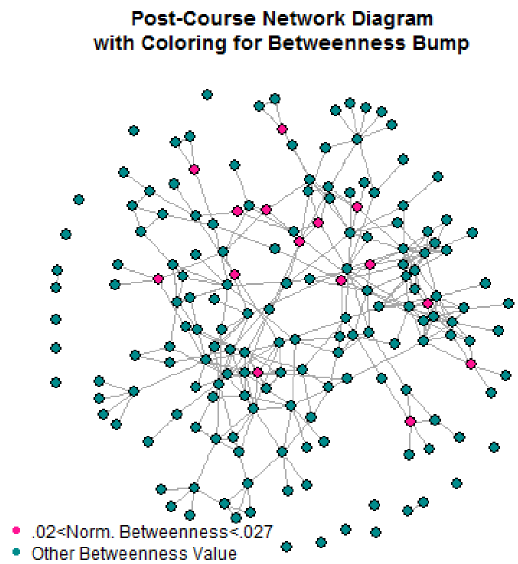


Figure 4.9: The portion of non-traditional students within the bump (betweenness between .02 and .027) are highlighted in this post-course network diagram. Many of them are connections to "fingertip" nodes in the network.

Log-Linear Closeness Plots Figure 4.10 shows the subsetted plots for cumulative closeness. Because of the large difference in pre- to post-course values, the plots have been plotted on separate axes. Traditional students have a similar shape. Additionally, students who were not connected in some way to the central network of the class (isolates) had such small closeness values that the plots were distorted. Due to shifting the x-axes, there is no data point at $y=1$. The intersection of the traditional plots implies that the rates of decay as the closeness values grow are different. The non-traditional plot does not have this trait and it appears that this group has a fairly consistent gain in closeness centrality. Traditional students with higher pre-course closeness did not show the same amount of gain in closeness that those with lower pre-course closeness did. Pre-course comparisons show that non-traditional students begin with lower closeness values. While they make gains in closeness, they do not seem to catch up to the traditional students' closeness values, unlike in degree centrality in Figure 4.7.

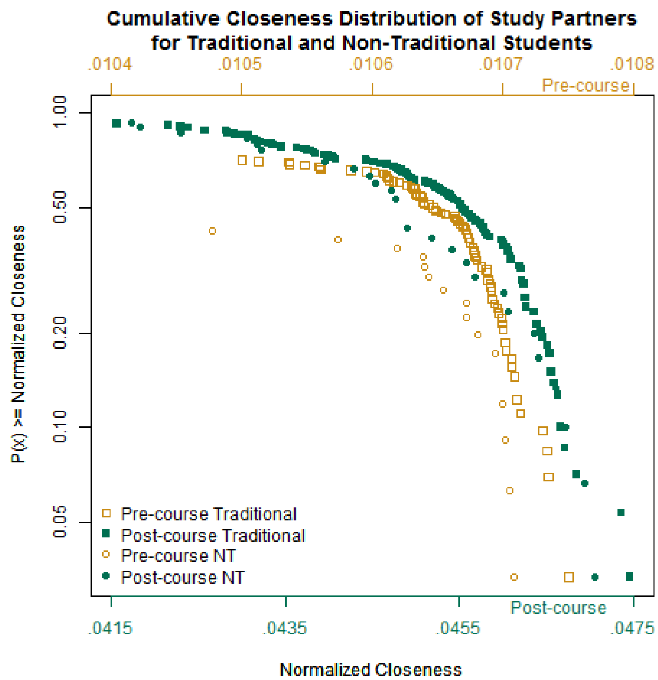


Figure 4.10: Logarithmic-linear plot of normalized closeness for non-traditional and traditional students. Non-traditional students start and finish the course with lower closeness than traditional students.

Log-Linear PageRank Plots Figure 4.11 displays subsetted plots of cumulative PageRank. The proportion of students with a lower PageRank is higher and continually drops as the PageRank centrality value increases. This result indicates that the students have better connected (more important) partners at the end of the course than they did at the beginning. There is some noise at PageRank > .020 due to a low n value, which has been cut from these plots. There are 10 data points in the pre-course traditional values that overcome the post-course values when PageRank is greater than .012. Overall, this plot shows a fairly steady relationship. Interestingly, for non-traditional students the pre-course has a significantly sharper decline than the post-course. There are only 8 data points that contribute the tail of this line so this could be a result of noise. The post-course plot appears quite steady but contains a bump at PageRank less than .005. Again, a gain from pre-to post-course is shown.

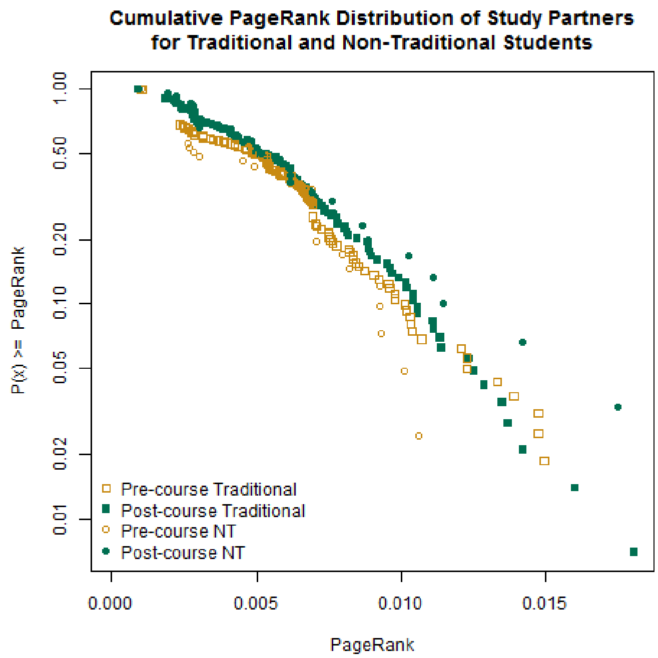


Figure 4.11: The subsetted PageRank values are plotted together. It appears the non-traditional students tend to have a slightly lower pre-course PageRank, but slightly higher post-course values. The values are overall very concentrated.

Alluvial Diagram

Alluvial diagrams show the flow dynamics of a changing system. In Figure 4.12 the reader can see how non-traditional and traditional students' pre- and post-course degrees changed. The salmon color represents traditional students, while green shows non-traditional students. Figure 4.12 separates non-traditional students from traditional students and allows the reader to track how non-traditional students have changed the size of their study networks from pre-course to post-course compared to traditional students. Following the green non-traditional students, it can be seen that almost all have indicated at least one study partner by the end of the semester. Note: Some error may occur due to students who may have completed the pre-survey, but not the post-survey. For example, a student may have identified 4 study partners at the start, but then only been identified by 1 other classmate, giving the impression that the student lost study partners, when in reality, the student may have increased his/her degree, but neglected to complete the post-course survey.

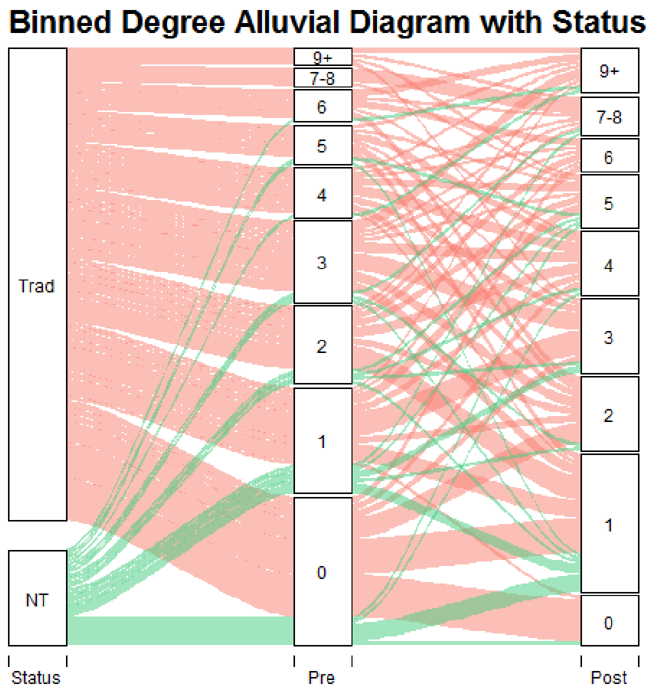


Figure 4.12: Binned alluvial diagram for pre- and post-course degree with status: shows the flow of non-traditional and traditional students' degree values from pre- to post-course. An overall gain appears as the sizes of the low value boxes are smaller and higher value boxes are larger.

Network Measurement Correlations, Statistics and T-Tests

Kendall and Spearman Correlation Methods to Compare Different Centrality Methods

Using the Kendall and Spearman correlation methods in R, the following correlation values were calculated with *n iterations= 1,000*. Because the p-values are all 0, these correlations confirm that the ordering of centrality measurements is not a random occurrence. That is to say, students with high degree centrality also have high betweenness, closeness, and PageRank centrality. Tables 4.3, 4.4, 4.5, and 4.6 contain the correlation, r, values describing the correlation between the various types of centralities. All p-values were 0. Comparing Tables 4.4 and 4.6 to Tables 4.3 and 4.5, respectively, shows that the Spearman method consistent yields higher correlation coefficients. Degree and PageRank have the most similar rankings which is logical since the network is undirected. Degree correlates fairly well with all centrality measures.

All other datasets had similar p-value results, so they will not be reported.

Table 4.3: Centrality correlation results using Kendall method: Pre-course

	Degree Pre	Betweenness Pre	Closeness Pre	PageRank Pre
Degree Pre	-	0.729	0.814	0.834
Betweenness Pre	-	-	0.693	0.630
Closeness Pre	-	-	-	0.622

Table 4.4: Centrality correlation results using Spearman method: Pre-course

	Degree Pre	Betweenness Pre	Closeness Pre	PageRank Pre
Degree Pre	-	0.840	0.924	0.927
Betweenness Pre	-	-	0.770	0.757
Closeness Pre	-	-	-	0.802

Table 4.5: Centrality correlation results using Kendall method: Post-course

	Degree Post	Betweenness Post	Closeness Post	PageRank Post
Degree Post	-	0.700	0.690	0.842
Betweenness Post	-	-	0.605	0.672
Closeness Post	-	-	-	0.520

Table 4.6: Centrality correlation results using Spearman method: Post-course

	Degree Post	Betweenness Post	Closeness Post	PageRank Post
Degree Post	-	0.850	0.846	0.944
Betweenness Post	-	-	0.779	0.849
Closeness Post	-	-	-	0.707

Network Statistics Table 4.7b summarizes the mean (and standard error) centrality values for pre- and post course networks for the full class and non-traditional/traditional status. Raw degree values are reported with standard errors because it is the most straightforward to interpret.

Table 4.7: SNA Statistics

(a) Number of nodes (n) and Degree Statistics

	n values			Pre-Course Degree		Post-Course Degree		Degree Gain		Pre-Course Norm. Degree		Post-Course Norm. Degree	
Type	Pre-Course	Post-Course	Gain	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	203	174	161	2.10	0.18	3.49	0.22	0.98	0.22	0.01039	0.00087	0.0202	0.0013
NT	41	30	27	1.41	0.29	3.57	0.61	1.81	0.56	0.0070	0.0014	0.0206	0.0036
Trad	161	144	134	2.28	0.21	3.48	0.23	0.81	0.24	0.0113	0.0010	0.00201	0.0013

(b) Normalized Betweenness, Closeness, and PageRank Statistics

	Pre-Course Norm. Betweenness		Post-Course Norm. Betweenness		Pre-Course Norm. Closeness		Post-Course Norm. Closeness		Pre-Course PageRank		Post-Course PageRank	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	0.00514	0.00091	0.0172	0.0019	0.00809	0.00020	0.04083	0.00091	0.00493	0.00029	0.00575	0.00027
NT	0.0029	0.0011	0.0173	0.0044	0.00717	0.00044	0.0422	0.0018	0.00415	0.00051	0.00593	0.00072
Trad	0.0057	0.0011	0.0172	0.0021	0.00834	0.00022	0.0405	0.0010	0.00511	0.00033	0.00571	0.00029

Relevant T-Tests: Degree T-tests were performed on the subsetted (by status) data and analyzed for differences in mean unnormalized degree. Logical reasoning holds that since the Kendall/Spearman correlations determined the various centralities do not shift the order of the centralities substantially, other t-tests on centralities would produce the similar results.

Table 4.8 shows a p-value less than .05. These data sets were tested using Cohen's d using a pooled standard deviation (details are listed in Chapter 3). The analysis revealed *d=0.346* which corresponds to a small effect size. Cohen [11] states that each of the sample sizes need to have 393 data points to ensure an effect is not missed. Since the non-traditional sample size is only 41 data points and the traditional sample size is also less than 393, it cannot be definitively stated that this result is a small effect size.

Table 4.8: P-values from t-tests for differences in degree centrality at pre- and post-course. Degree gains were also tested. The data is subset by non-traditional status. Note the bolded p-value less than .05.

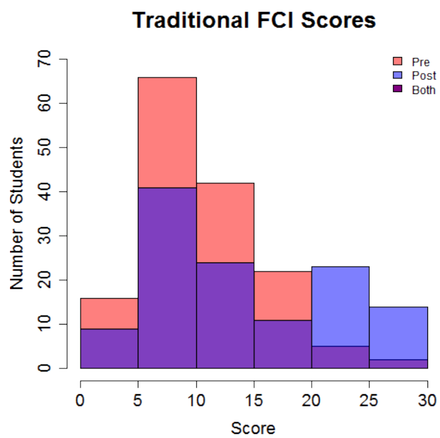
Fall 2014		Non-Traditional Degree		
		Pre-Course	Post-Course	Gain
Traditional Degree	Pre-Course	**0.01641**	-	-
	Post-Course	-	0.8945	-
	Gain	-	-	0.1107

4.1.3 FCI Statistics and Diagrams

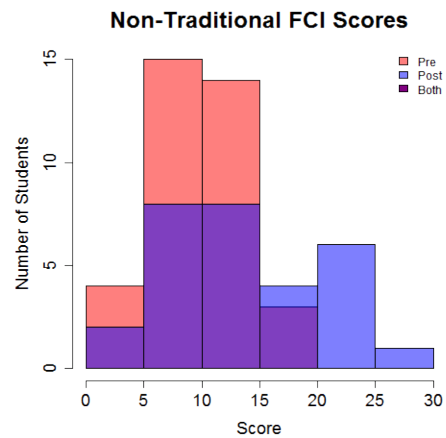
The individual analysis of FCI pre- and post-course scores along with gains are presented in the form of histograms, boxplots, alluvial diagrams, and numeric data tables.

Histograms

A comparative look at traditional vs. non-traditional students pre- and post-course gains, as shown in Figure 4.13, allows the reader to see that generally both types of students show a rightward shift. This is expected and positive, as it means that after instruction students answer questions about force concepts more accurately than without instruction. Additionally the figure suggests that non-traditional students seem to have had a higher proportion of students with large FCI gains than the traditional students did. Although the FCI post distribution also is shaped significantly differently for non-traditional students than traditional students, the shapes of each status-separated figure seem to stay somewhat consistent from pre- to post-course.



(a) Pre- and post-course FCI scores for traditional students. Students seem to have gained, and the plot has a similar shape from pre- to post-course.



(b) Pre- and post-course FCI scores for non-traditional students. The post-course plot is similarly shaped over a broader range than the pre-course shape and non-traditional students seem to have gained more conceptual knowledge.

Figure 4.13: Pre- and post-course FCI scores for each status are displayed.

Figure 4.14 shows how non-traditional (maroon) students have progressed from the FCI as a pre-test to a post-test compared to traditional (yellow) students. The histogram also reflects the class-wide average gain of approximately 4. Analysis has shown this value to be 4.22 (see Table 4.9), meaning that for the students who took both pre- and post-course FCIs, an average four additional questions were answered correctly. It is also interesting to note the shape of the non-traditional students' gain. It does not tend to be a normal distribution, but rather a level value spanning the range.

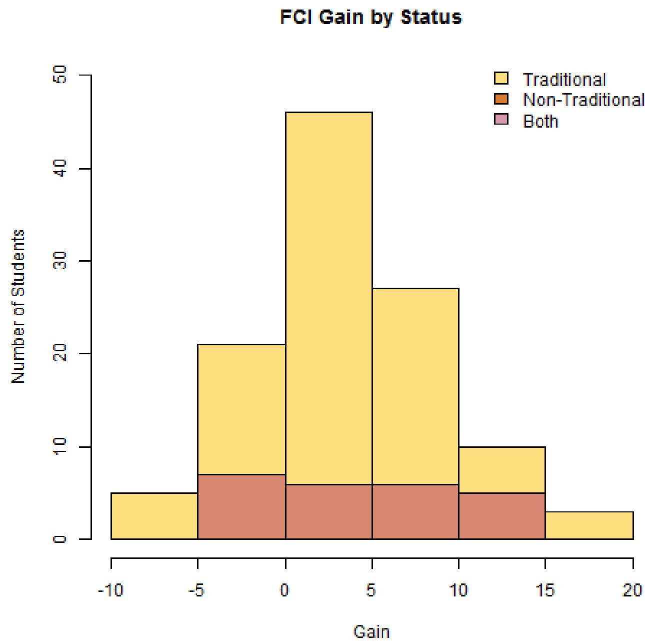


Figure 4.14: A histogram of FCI gains colored by status and centered around a gain of approximately 4. The histograms are overlaid. Non-traditional students have similar values to traditional students, but a nearly uniform distribution.

Boxplots

Traditional students' pre-course FCI results are shown in Figure 4.15. Comparing the median values of the boxplots, the median from pre- to post-course has shifted toward a higher score. There is also a wide range of values for post-course scores.

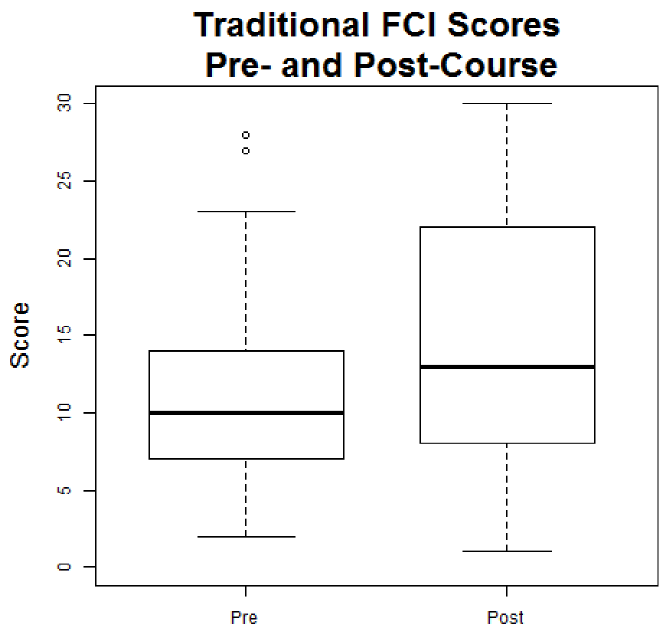


Figure 4.15: FCI scores for traditional students for pre- and post-course FCI. A positive shift in median is shown. The box's widths correspond to sample sizes.

The non-traditional student version of Figure 4.15 is shown in Figure 4.16. An upward shift in median is shown in this figure as well and the range of post-course FCI scores is smaller.

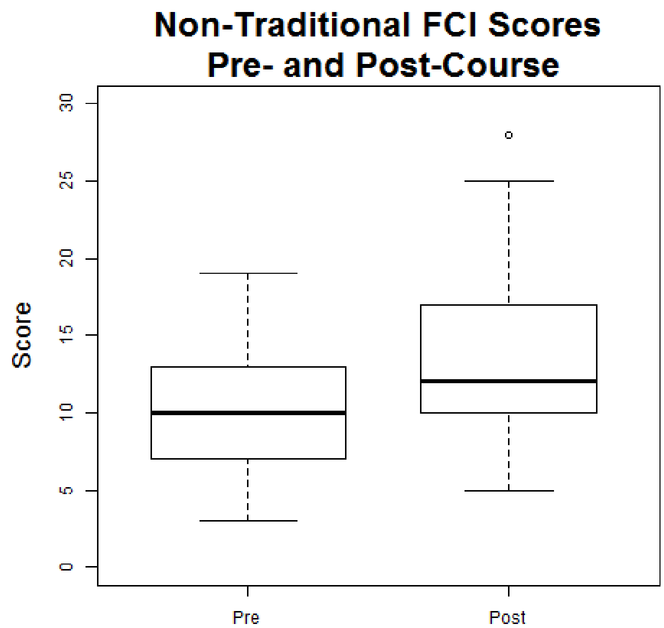


Figure 4.16: FCI scores for non-traditional students for pre- and post-course FCI. Again, a positive shift in median is shown and appears slightly greater than that of Figure 4.15.

Figure 4.17 contains boxplots of the FCI score gains for each subset. Since traditional students had a higher *n* value, it is logical that they have a wider range. The median values are fairly equal, but non-traditional students appear to have a slight edge. The wider middle quartile range for non-traditional students can be attributed to the small sample size (*n*=*24*).

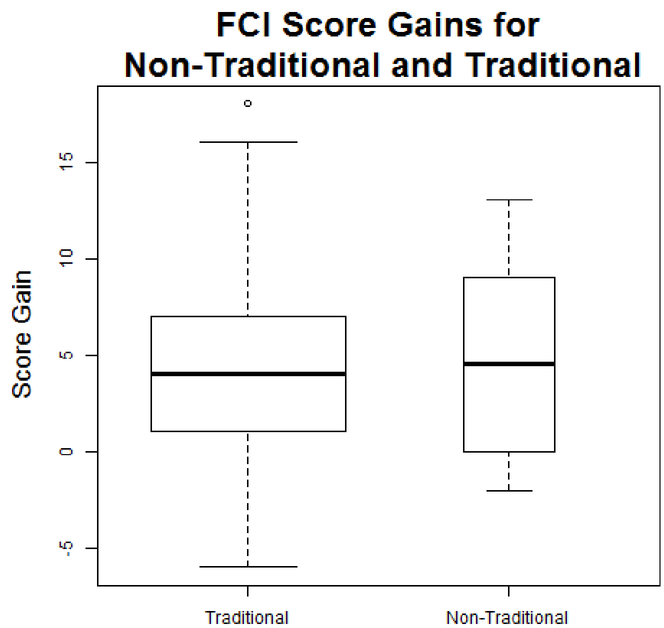


Figure 4.17: FCI score gains for traditional and non-traditional students. Traditional students have a wide range of values and a slight difference in median gain can be seen with non-traditional students improving their scores slightly more. The non-traditional box is thinner because there are fewer students in the sample.

Alluvial Diagram

Figure 4.18 shows how non-traditional (maroon) students' scores have progressed from the FCI as a pre-test to a post-test compared to traditional (gold) students. FCI scores have been grouped multiples of 5 in this figure to simplify the diagram. It appears that non-traditional students have a bit less conceptual knowledge coming into the course (with none scoring above 15), but learn concepts throughout the course and are well distributed in the post-course bins. Traditional students show overall gains as well, meaning the majority of the class seemed to increase their conceptual knowledge by the end of the course.

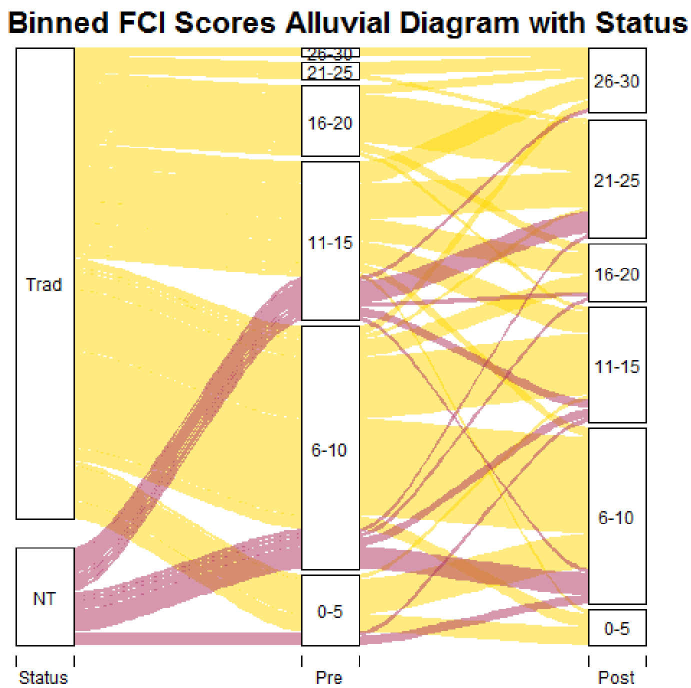


Figure 4.18: Alluvial Diagram for Pre- and Post-Course FCI Scores with Status Binned: displays the flow of conceptual learning from pre- to post-course for traditional and non-traditional students. Overall, conceptual learning appears as there are smaller sized low FCI score bins in the post-course columns.

FCI Statistics and T-Tests

The sample sizes and descriptive statistics for the pre- and post-course FCI as well as gains for both subsets and the entire class are in Table 4.9. The mean values of FCI gain confirm that non-traditional students had a higher mean gain from Figure 4.17.

Table 4.9: FCI Statistics

	n values			FCI Pre-Course		FCI Post-Course		FCI Gain	
Type	Pre-Course	Post-Course	Gain	Mean	Standard Error of Mean	Mean	Standard Error of Mean	Mean	Standard Error of Mean
All	191	152	136	10.79	0.35	14.36	0.61	4.30	0.43
NT	36	29	24	10.11	0.66	13.9	1.2	5.17	0.99
Trad	153	122	112	10.95	0.41	14.52	0.70	4.12	0.46

T-tests were completed on pre-course, post-course and conceptual gain mean values between non-traditional and traditional subsetted data to determine if any differences between the subsets were significant. Results shown in Table 4.10 indicate no significant differences in the group means. While Figure 4.18 and Table 4.9 suggested that non-traditional students may have started with lower conceptual knowledge and had higher gains, respectively, the t-tests determined the differences in means for non-traditional and traditional students is not significant.

Table 4.10: P-values from t-tests for FCI pre-course, post-course and FCI gains for Dataset A. No p-values are less than .05.

Fall 2014		Non-Traditional FCI		
		Pre-Course	Post-Course	Gain
Traditional FCI	Pre-Course	0.2824	-	-
	Post-Course	-	0.6659	-
	Gain	-	-	0.3436

4.1.4 FCI and Network Correlations and Statistics

A reduced set of data was established for those students in the pre- and/or post-course network who also had FCI data. Correlations and statistical analysis results follow.

Pearson Correlation Tests on FCI and Degree Centrality

Pearson correlation (*n iterations = 10,000*) tests were completed in an attempt to correlate FCI scores for pre- and post-course and score gain to degree centrality values at pre- and post-course and degree gain. Since the correlations reported in Tables 4.3, 4.4, 4.5, and 4.6 have determined that the various centrality measures rank nodes' centralities in a similar order, correlations with only degree centrality are sufficient for this analysis.

There were several correlations in Table 4.11 with p-values less than .05. Using the corresponding correlation values and Cohen's guidelines for determining effect size, the effect size for all of them appears to be small. A sample size of 783 would be needed to prove that this was not an effect [11].

These correlations indicate that for all pre-course groups, students who had more study partners had, on average, a lower level of conceptual knowledge. When traditional students are included in the data, a significant negative correlation exists between FCI pre-course scores and post-course degree centrality values. This was also true for pre-course degree centrality values. The fact that non-traditional students do not experience this phenomena at a significant level is interesting, but not necessarily meaningful. The most interesting result in Table 4.11 is the negative correlation between traditional students' post-course FCI and degree values. It appears that their post-course connections still do not lead to higher levels of conceptual knowledge which is contradictory to the research presented in Chapter 3 [8].

		All Data					
		FCI Pre-Course		FCI Post-Course		FCI Gain	
		r	p-value	*r*	p-value	*r*	p-value
All Data	Pre Degree	**-0.201**	**0.0077**	-0.154	0.069	-0.079	0.373
	Post Degree	**-0.230**	**0.0052**	-0.164	0.0587	-0.0374	0.688
		Non-Traditional Data					
		FCI Pre-Course		FCI Post-Course		FCI Gain	
		r	p-value	*r*	p-value	*r*	p-value
Non-Traditional	Pre Degree	**-0.201**	**0.0069**	-0.281	0.184	-0.298	0.178
	Post Degree	-0.281	0.195	- .00984	.971	-0.765	0.603
		Traditional Data					
		FCI Pre-Course		FCI Post-Course		FCI Gain	
		r	p-value	*r*	p-value	*r*	p-value
Traditional	Pre Degree	**-0.192**	**0.019**	-0.141	0.138	-0.0389	0.687
	Post Degree	**-.225**	**0.0097**	**-0.190**	**0.0463**	-0.0401	0.696

Table 4.11: Pearson Data Correlations For Degree and FCI values for full data and subsetted data. Bolded p-values are less than .05.

FCI and Network Statistics

n values and basic statistics for the dataset of students with FCI and network data are presented in Table B.1 in Appendix B. No values appear to be substantially different.

4.2 Dataset B Results

Only select details for other datasets are presented. Additional results and figures can be found in Appendix B.

This class was instructed in the same large, traditional lecture classroom that the Dataset A class was as an early evening class. A separate one hour recitation met once weekly. Lectures were twice weekly for an hour and twenty minutes. The instructor used a traditional lecture format with no peer cooperation or group problem solving strategies. No FCI data was collected for this section, therefore only network analysis will be discussed.

	Pre-Course	Post-Course
Class Size	193	188
Network Survey Response Rate	0.85	0.83

Table 4.12: Response rates for the data collected are shown. Surveys were completed outside of class as an extra credit opportunity for students.

4.2.1 Network Data

Table 4.13 provides values of the number of nodes and edges in Dataset B pre-course and post-course networks. Despite a small decrease in the number of students, more connections were reported. This implies that the network is more connected at the post-course than it was at the pre-course. The network density values confirm that implication.

		Pre-Course	Post-Course
Number of	Nodes	185	177
	Edges	288	327
Network Density		0.017	0.021

Table 4.13: Number of nodes and edges (student identified connections) in Dataset B. Post-course has slightly fewer nodes, but more connections were reported indicating a more connected study network at the end of the course, as evidenced by the network density increase.

4.2.2 Network Diagrams and Statistics

Figure 4.19 provides only network data and student non-traditional status, unlike previous colored versions of network diagrams, no FCI data was taken. There are two high degree students in this network with one large connected network object, a few dyads and many isolates (12 percent of the nodes, which is lower than many published results that analyzed lecture courses).

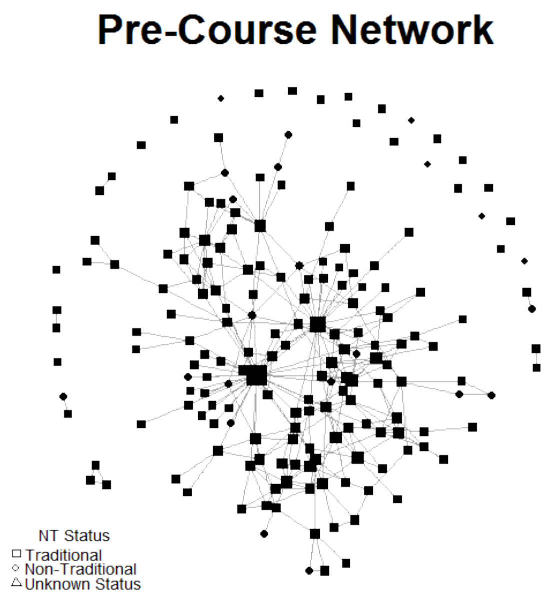


Figure 4.19: The pre-course network is sized by post-course degree centrality value and shaped by student non-traditional/traditional status. There are 185 nodes with 22 of them being non-traditional students. There are many isolates and one large central network with two high degree centrality students.

Figure 4.20 shows the post-course network. Nodes are shaped by their status as traditional or non-traditional students and sized by post-course degree centrality values. The network appears to be more connected than Figure 4.19. Now only one central student is prominent.

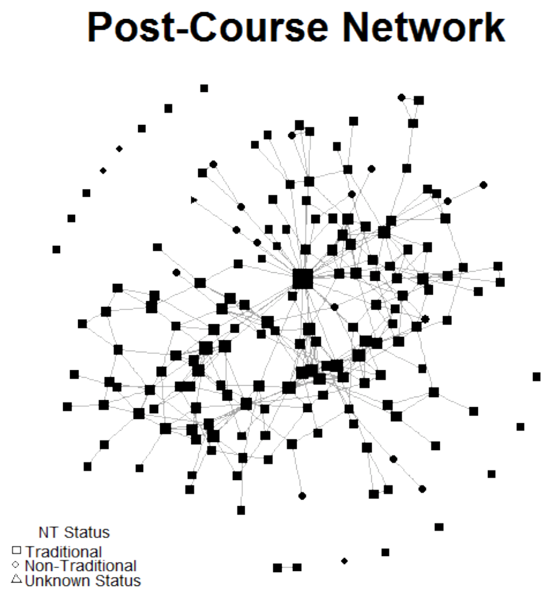


Figure 4.20: The post-course network is sized by post-course degree centrality values and shaped by student non-traditional/traditional status. There are 177 nodes with 19 of them being non-traditional students and one student has prominent degree centrality over the rest.

Log-Linear Plots

Subsetted and superimposed logarithmic-linear cumulative plots for non-traditional and traditional students are below.

Log-Linear Degree Plots Figure 4.21 has been trimmed to cut out noise at degree values greater than 12 (omitting 2 pre-course traditional and 1 post-course non-traditional data point). The result is a linear relationship displaying small degree gains for traditional students. Non-traditional students appear to maintain their study relationships when they have less than 4 partners. Non-traditional students consistently have less partners than traditional students.

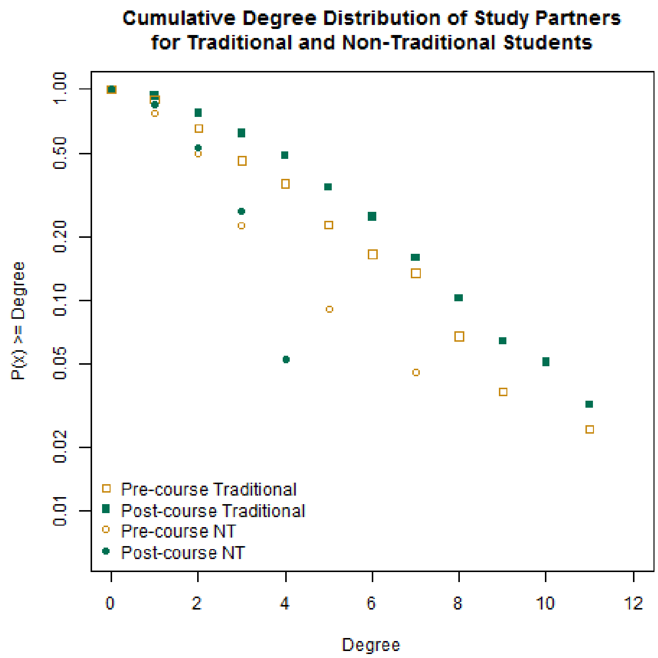


Figure 4.21: CDF of non-traditional and traditional students show that traditional students consistently have more study partners and have a slight gain in the number of partners from pre- to post-course. Noise has been eliminated from this plot (3 data points removed). (Pre-course: NT=22, Trad=163. Post-course: NT=19, Trad = 157.)

Log-Linear Betweenness Plots Figure 4.22 shows the CBF for this dataset. Due to noise, this plot has been rescaled to only show general trends. Traditional students consistently have higher betweenness centrality. Both sets of data appear to gain betweenness centrality from pre- to post-course, which is particularly interesting for non-traditional students. Despite maintaining or losing the number of connections, they now are positioned between more nodes, suggesting they may have higher closeness values.

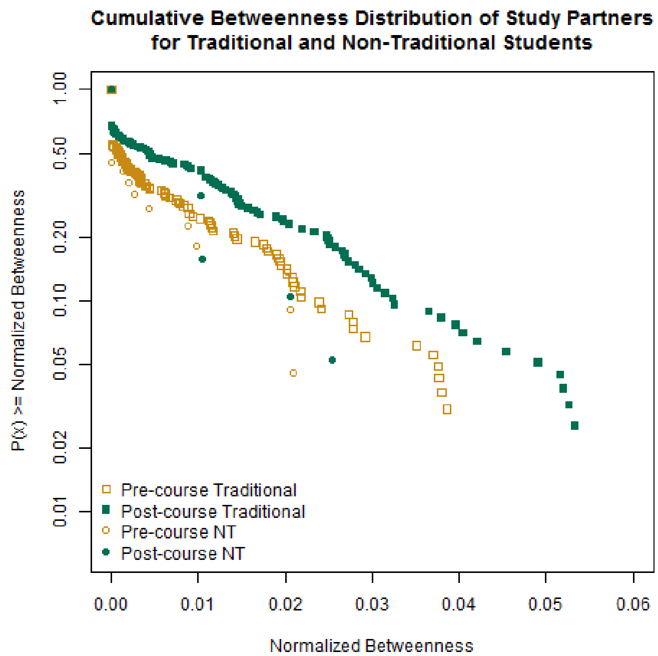


Figure 4.22: Non-traditional and traditional student subsets are overlaid. Both sets of students gain betweenness centrality, but traditional students gain more and have higher betweenness centrality at pre- and post-course times. Seven values were removed from this plot to cut down on noise.

Log-Linear Closeness Plots The log-linear closeness plot for this dataset had a similar shape to that of Dataset A's (see Figure 4.10, so it has been moved to Appendix B. Non-traditional students do have higher post-course closeness values. In fact, both groups gain closeness, though non-traditional students have lower pre- and post-course values than traditional students.

Log-Linear PageRank Plots Similar to Figure 4.22, noise has been removed from Figure 4.23 by limiting the x-axis range. Non-traditional students start and end the course with lower PageRank centrality than traditional students, meaning that the connections non-traditional students make are not as well connected as those that traditional students make. Traditional students tend to gain PageRank, making better connected connections, while non-traditional students lose some PageRank centrality.

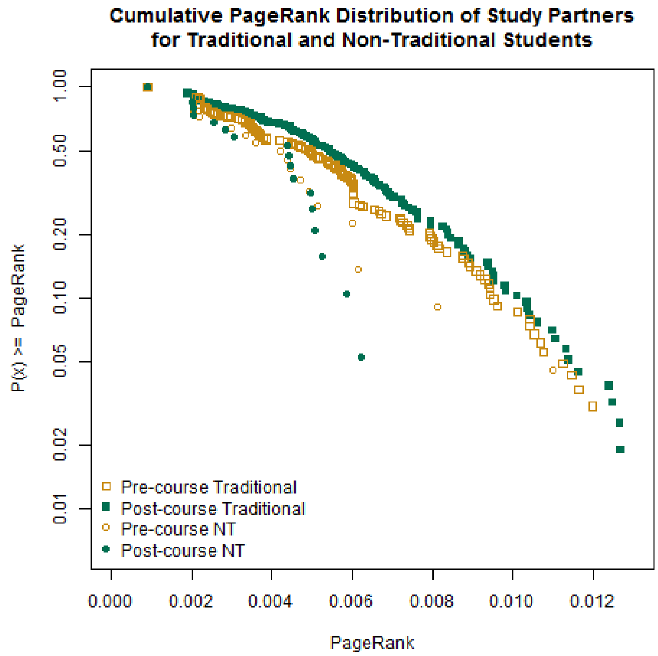


Figure 4.23: The PageRank plots for this data set show very concentrated values. It appears the non-traditional students tend to have a lower PageRank than traditional students. Pre- to post-course trends show gains for traditional students and losses of PageRank centrality for non-traditional students. Six data points were omitted from the plot to eliminate noise.

Alluvial Diagram

Figure 4.24 shows the flow of students degree values from pre- to post. As suggested by Figure 4.21, losses in non-traditional students' degrees are found, unlike the results from Dataset A. Traditional students have a multitude of changes in degree centrality values, therefore no generalizations can be made. This may be due to the lack of encouragement within the course for peer cooperation.

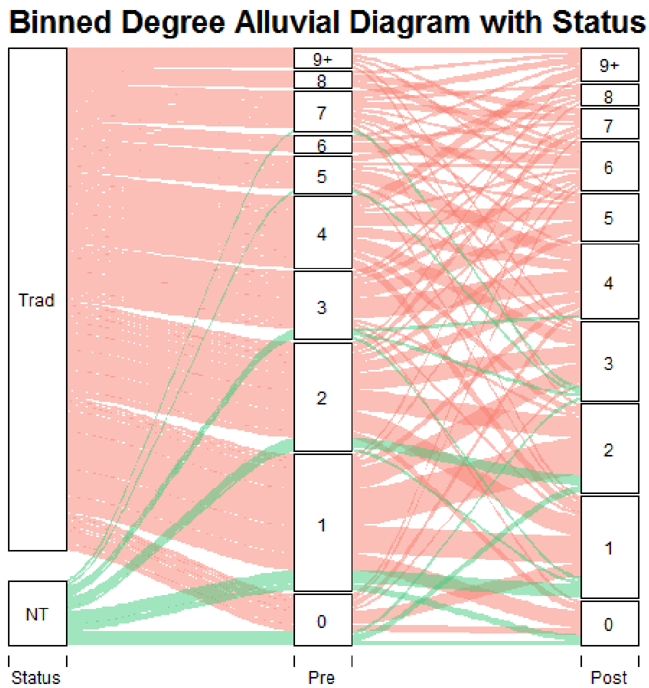


Figure 4.24: Binned Alluvial Diagram for Pre- and Post-Course Degree with Status: shows the flow of non-traditional and traditional students' degree values from pre- to post-course. The diagram indicates that non-traditional students lose study partners throughout the course with a wide variety of changes occurring in the traditional student subset.

Tables of Network Statistics and T-Tests

The full table of network statistics is printed in Appendix B. Previous evidence of non-traditional students' degree loss and small traditional students' gain is confirmed by the values.

T-tests were performed on the subsetted (by status) data and analyzed for differences in unnormalized degree pre- and post-course. Logical reasoning holds that since the Kendall/Spearman correlations determined the various centralities do not shift the order of the centralities substantially, other t-tests on centralities would produce the same results.

Table 4.14: P-values from t-tests for degree centrality at pre- and post-course. The data is subset by non-traditional status. Note p-values less than .05.

Fall 2014		Non-Traditional Degree Pre-Course	Non-Traditional Degree Post-Course
Traditional Degree	Pre-Course	0.0026	-
	Post-Course	-	1.7E-7

Table 4.14 shows p-values less than .05. The analysis revealed *d=0.396* for pre-course degree which would be considered a small effect size. A sample size of 393 would be needed to ensure a larger effect size was not missed. (There are 22 non-traditional points and 163 traditional points.) The post-course degree analysis found *d=0.653* which corresponds to a medium effect size. Without having 64 points (non-traditional data only contained 19 points) it cannot be definitively stated that this is a medium effect size.

4.3 Dataset C Results

This section was instructed by the same professor as Dataset A in a smaller classroom meeting three days a week in the early morning for an hour and forty minutes with an integrated recitation. The class size was capped at thirty-six students. The classroom was setup with seating in groups of six with computers for all students in a SCALE-UP setting. The instructor utilized peer instruction and cooperation throughout teaching, combined with lecturing and computer activities. Basic class information and response rates are given in Table 4.15.

		Pre-Course	Post-Course
Class Size		36	29
Response Rate	FCI	0.69	0.59
	Network Survey	0.67	0.72
	FCI and Network	0.67	0.59

Table 4.15: Response rates for the data collected are shown. It is possible that these rates are lower than other sections due to the summer semester schedule. Some students enrolled in the class and did not attend on the day the FCI was given.

4.3.1 Network Data

Table4.16 provides values of the number of nodes and edges for pre-course and post-course networks. While the number of nodes remains fairly constant, that does not mean the nodes are necessarily representing the same group of students. The pre- to post-course comparison demonstrates growth in the number of connections of the identified nodes and is confirmed by the higher post-course network density.

		Pre-Course	Post-Course
Number of	Nodes	28	29
	Edges	29	47
Network Density		0.0767	0.116

Table 4.16: Number of nodes and edges (student identified connections) in Dataset C. The post-course survey identified a large increase in the number of identified connections, creating a higher network density.

Network Diagrams and Statistics

Figure 4.25 has a ring shape with some isolates. While it may appear that this is a well connected network, there are many nodes that information has to flow through to reach students on the other side of the ring. Many nodes have similar sizes meaning similar numbers of study partners at the start of the course. It is interesting that there are more non-traditional students connected to this ring than what previous datasets have shown.

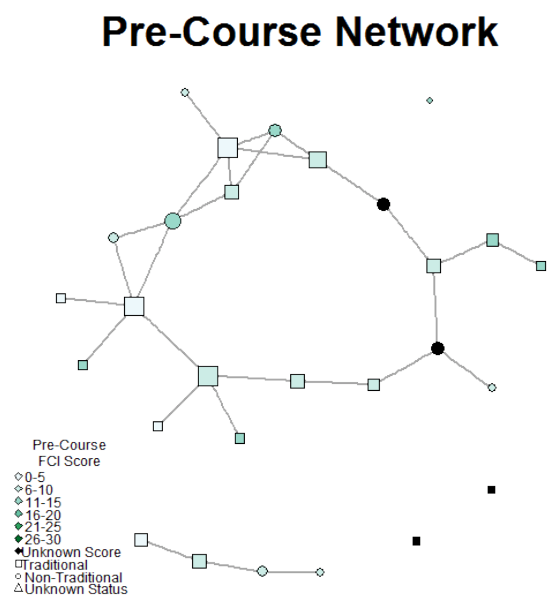


Figure 4.25: The pre-course network shows a variety of incoming knowledge and an interesting ring shape of connections which include both student types. There are 28 nodes with pre-course FCI scores for 24 of them.

Figure 4.26 shows a more connected network that has lost the ring shape shown in Figure 4.25. For the available FCI gains, we see that many students have gained knowledge with only a few losing concepts throughout the course. There are less isolates in the post-network and it seems like non-traditional students have moved to the outskirts of the network.

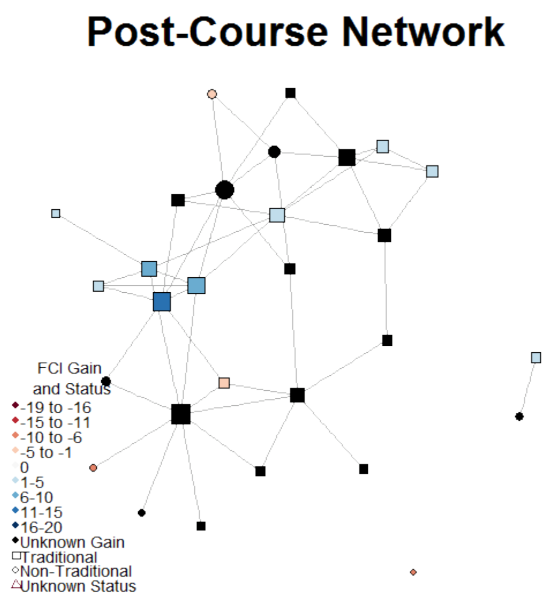


Figure 4.26: The post-course network is colored by FCI score gain values, sized by post-course degree centrality values, and shaped by student non-traditional/traditional status. There are 29 nodes with FCI gain values for 12 of them.

Log-Linear Plots

It is important to be conscious of the lower n values in this dataset. In some places, non-traditional students in the post-course for example, there are only five data points, so the determination of general trends in the cumulative centrality plots should be taken lightly.

Log-Linear Degree Plots Figure 4.27 reflects a gain in degree for traditional students from pre- to post-course. It appears that both groups start with roughly the same degree centrality value, but traditional students seem to have larger gains.

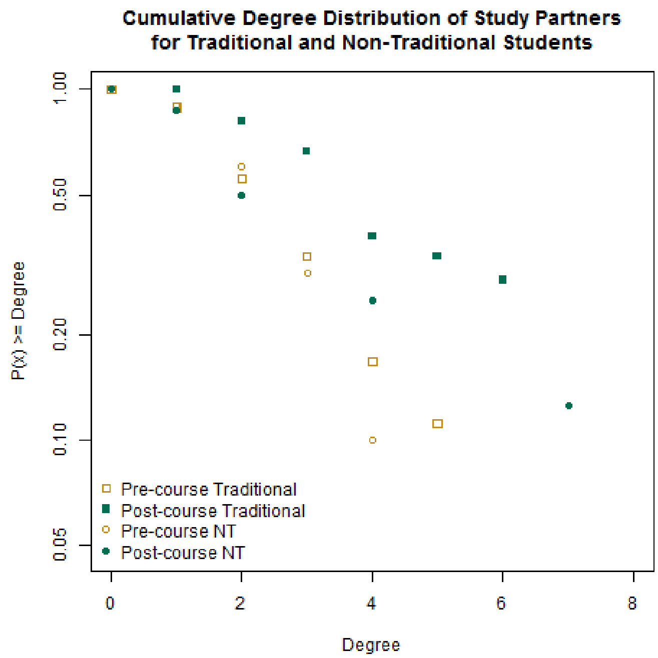


Figure 4.27: The logarithmic cumulative degree of non-traditional and traditional students are superimposed to show their trends from pre- to post-course. The two groups appear to have comparable shapes with non-traditional students having slightly lower numbers of study partners. Note that small n values exist here and one post-course traditional data point was eliminated to cut down on noise. (Pre-course: NT=10, Trad=18. Post-course: NT=7, Trad = 21.)

Log-Linear Betweenness Plots Figure 4.28 shows the disjoint of the ring and isolates at the pre-course. For those outside of the ring, the betweenness is low, but inside the ring, students have high betweenness because there are no cross-ring connections. At post-course, the anticipated linear relationship is seen with those inside the ring losing betweenness centrality and those outside the ring gaining centrality due to the changed network structure. Non-traditional students were slightly below traditional students at the pre-course and are significantly below at the post-course which confirms the observation discussed in analysis of the post-network. Two data points (with high degree values) were cut in order to remove noise (one from pre- and post-course traditional students).

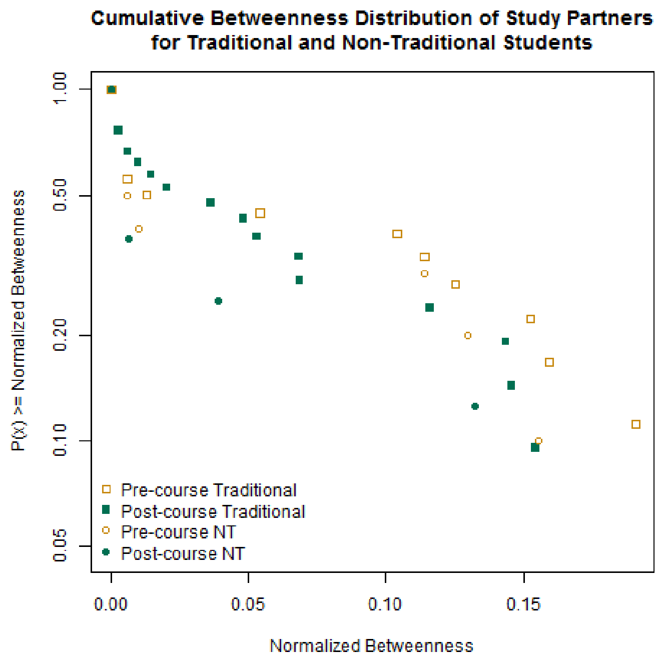


Figure 4.28: The betweenness plots reflect the pre-course ring with 2 separate tiers of betweenness values. Post-course values give a more linear result with traditional students significantly higher than non-traditional.

Log-Linear Closeness Plots Figure 4.29 shows the closeness distribution for traditional and non-traditional students at the pre- and post-course with extremely low closeness values omitted from the plotting region. Post-course trends reveal that non-traditional students have significantly lower closeness values, as predicted by the description accompanying Figure 4.26. Pre-course values are comparable. The shapes of the plots are identical.

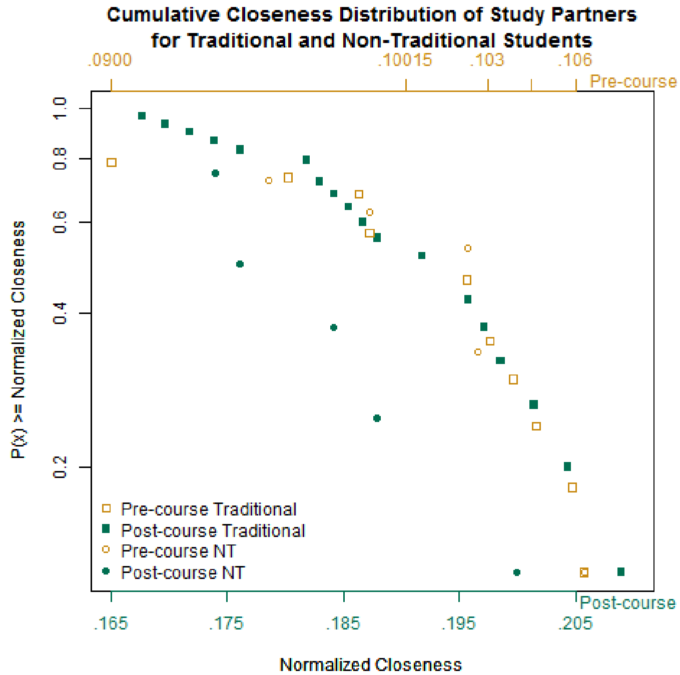


Figure 4.29: Closeness distribution is plotted with pre- and post-course on separate scales. The similar shape is well depicted and the post-course trend of non-traditional students being on the outskirts of the network is evident.

Log-Linear PageRank Plots The PageRank plot for this dataset did not show a specific (such as linear) trend and has been omitted.

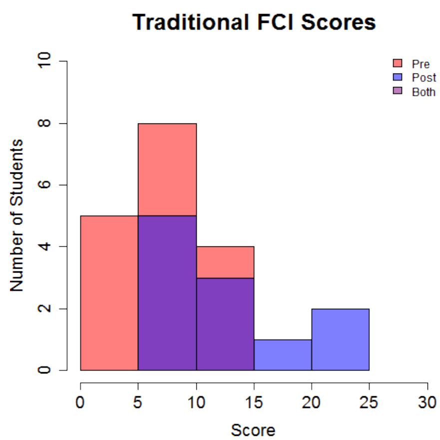
Tables of Network Statistics

The network statistics table is printed in Appendix B. No t-tests on non-traditional and traditional students' centralities yielded p-values less than .05.

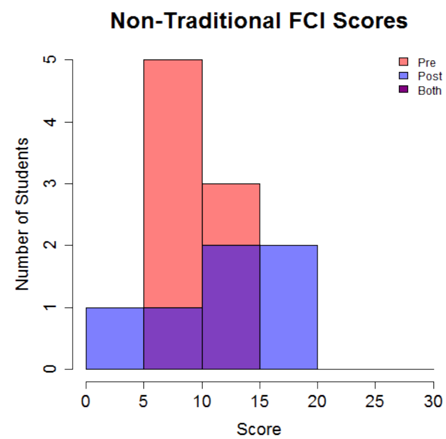
4.3.2 FCI Statistics and Diagrams

Histograms

A comparative look at traditional vs. non-traditional students pre- and post-course gains, as shown in Figure 4.30, shows that traditional students have undergone a rightward shift, indicating a gain in conceptual knowledge. Non-traditional students began in a very concentrated distribution and have flattened some by the post-course survey. This could suggest that the class format did not benefit non-traditional students as much as it did traditional students, but with low n values, that is difficult to determine. Datasets are not matched by students (so a student who dropped the class after the first week will be included in pre-course values).



(a) Pre- and post-course FCI scores for traditional students. Traditional students seem to have gained conceptual knowledge as indicated by the rightward shift. The pre- to post-course distribution also shifted from a normal distribution to a non-normal distribution.



(b) Pre- and post-course FCI scores for non-traditional students. The post-course only contains 6 data points, but the distribution from pre- to post-course has broadened fairly equally with gains seeming somewhat stagnant.

Figure 4.30: Pre- and post-course FCI scores for each status are displayed.

In Figure 4.31 non-traditional students appear to have lost some of their pre-course knowledge: an unanticipated result. This is a normally distributed class gain plot, but shows two definitively different shapes for the subset data. Traditional students appear to have gained more conceptual knowledge throughout the course unlike non-traditional students.

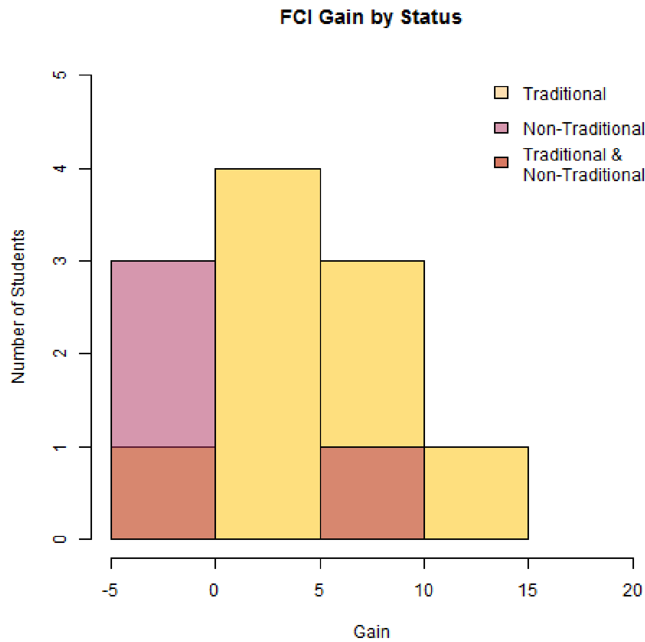


Figure 4.31: A histogram of FCI gains colored by status depicting very different distributions of gains for subsetted data.

FCI Statistics

The sample sizes and basic statistical values for the pre- and post-course FCI as well as gains for both subsets and the entire class are listed in Appendix B. No t-tests on non-traditional/non-traditional FCI pre- or post-course or gain scores indicated significant results, despite the suggestion in Figures 4.30 and 4.31.

4.3.3 FCI and Network Data Combined

Pearson Correlation Tests on FCI and Degree Centrality

Correlations between pre- and post-course degree values and FCI scores and gains are reported in Appendix B. Two had p values less than .05. For the full dataset, post-course (*r=0.587*) and gain (*r=.729*) in degree had significant and positive correlations with post-course degree which was anticipated. The correlations indicate that a higher post-course number of study partners should have a higher post-course FCI score and more FCI gain. (More partners = more conceptual knowledge and learning.) Each corresponds to a large effect size.

FCI and Network Statistics

n values and basic statistics for the dataset of students with FCI and network data are presented in Appendix B.

4.4 Dataset D Results

This class took place in a large traditional lecture hall with seating for 200 with a different instructor than any other section presented. The class met three times per week with a separate recitation section meeting once weekly. Each meeting session was 55 minutes long. The instructor utilized a traditional lecture style format for the course.

		Pre-Course	Post-Course
Class Size		118	104
Response Rate	FCI	0.81	0.66
	Network Survey	0.41	0.28
	FCI and Network	0.47	0.44

Table 4.17: Response rates for the data collected are shown. Rates for this section of network data are significantly lower than other sections. It is believed this is due to the lack of incentive to complete the survey on students' personal time. (The instructor offered no extra credit for responding to the survey.)

Due to the low response rate for network data, only FCI data will be reported.

4.4.1 FCI Statistics and Diagrams

Alluvial Diagram

The alluvial diagram for this dataset resembles that of Dataset A, so it has been moved to Appendix B. It reflects a gain in knowledge from pre- to post-course. It appears that non-traditional students are well distributed in their incoming knowledge, having relatively the same proportions as traditional students in the pre-course bins.

Histograms

This figure is similarly shaped to Figure 4.13 from Dataset A, so it has been moved to Appendix B. Comparing traditional and non-traditional students' pre- and post-course gains depicts a rightward shift for both student types. This is expected and positive, as it means that after instruction students answer questions about force concepts more accurately than without instruction. The non-traditional post-course results indicate a wide variety of student learning throughout the course in a non-normal distribution. The traditional students show a more normal pre- and post-course distribution.

Figure 4.32 depicts an overall net gain of approximately 5 for both student types. Non-traditional students seem to have fared equally as well as, if not better than, traditional students, which provides an insightful look into the effects of a classroom with no integrated peer instruction by the professor. This implies that traditional lecture courses may be more effective in teaching concepts to non-traditional students.

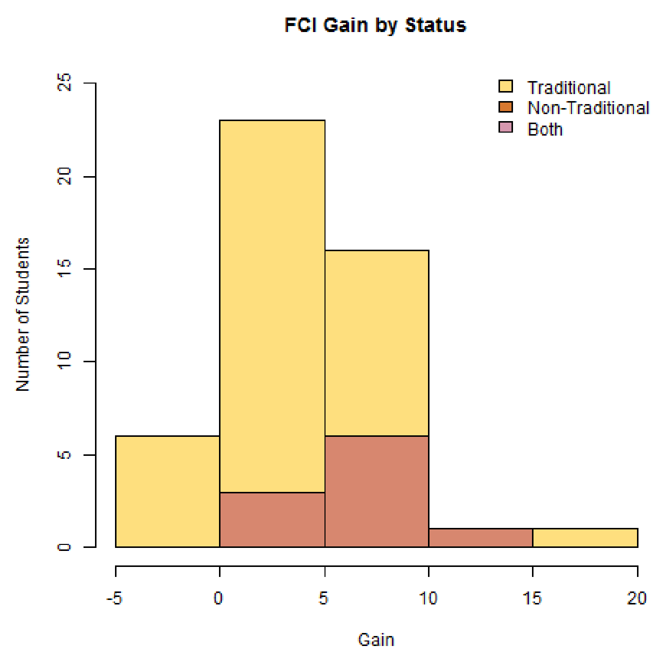


Figure 4.32: A histogram of FCI gains colored by status indicating a gain centered around 5. Shapes of the different statuses are mostly similar, with non-traditional shifted more rightward.

FCI and n-values

These are listed in Appendix B.

T-tests were completed on pre-course, post-course and conceptual gain values between non-traditional and traditional subsetted data. Results with $p<.05$ were found for the FCI pre-course scores between non-traditional (*14.2*) and traditional (*11.3*) students, where $p=0.0398$. With 66 datapoints in each subset, a medium effect size would be ensured as $d=0.511$.

Despite the presented results alluding to a significant difference in conceptual gain between non-traditional and traditional students, statistical analysis does not indicate that such a difference is indeed significant.

4.5 Dataset E Results

This class took place in a large SCALE-UP classroom where circular tables with individual computers and seats for six students per table. The room held 100 students, but the course never contained that many. Students were grouped during the first week of class and given assigned tables. The instructor used the previous described combination teaching methods of lecture, computer simulation and activities, peer instruction and group cooperation. This course included several undergraduate learning assistants: a new addition for the new classroom environment. The class met 3 times a week for an hour and twenty minutes with a recitation section built into that classtime. Table 4.18 give basic information about the course size and survey response rates.

		Pre-Course	Post-Course
Class Size		70	71
Response Rate	FCI	0.80	0.63
	Network Survey	0.86	0.61
	FCI and Network	0.57	0.45

Table 4.18: Response rates for the data collected are shown. Rates for this section of combined FCI and network data are significantly lower than other sections. It is believed this is due to poor class attendance.

4.5.1 Network Data

Table 4.19 provides values of the number of nodes and edges in the pre-course and post-course networks. It was expected that the post-course would be more connected than the pre-course network due to the high rate of in-class encouragement to work with others at students' tables and results from Dataset A. These values do not show that growth.

		Pre-Course	Post-Course
Number of	Nodes	69	63
	Edges	69	70
Network Density		0.0294	0.0358

Table 4.19: Number of nodes and edges (student identified connections) in Dataset E. Despite a large instructional emphasis on group problem solving and peer cooperation, the network density did not grow significantly. (The density is higher, but the number of nodes is smaller.)

4.5.2 Network Diagrams and Statistics

Figure 4.33 shows a y-shaped network object with many isolates and disconnected pairs/trios of study partners. The students that have a good pre-course knowledge of physics are grouped together. Non-traditional students appear to be well mixed in the network and as isolates. There are two sub-networks in this figure that, if students mingled, could create one larger network of knowledge sharing.

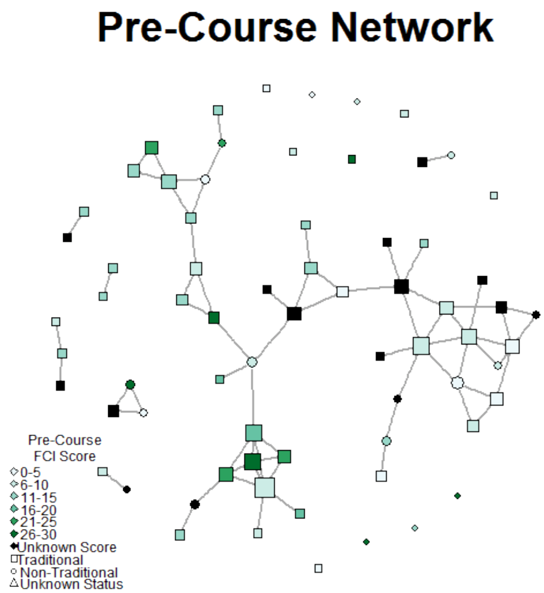


Figure 4.33: The pre-course network is colored by FCI pre-course scores, sized by pre-course degree centrality value, and shaped by student non-traditional/traditional status. There are 69 nodes with pre-course FCI scores for 56 of them. Note that students with lots of pre-course knowledge are grouped together.

Figure 4.34 gives the post course network which shows a more dispersed network. While more nodes are connected somewhere, there are no cross-network edges. From this diagram, betweenness centrality should be high for the one non-traditional student that connects the two smaller networks together.

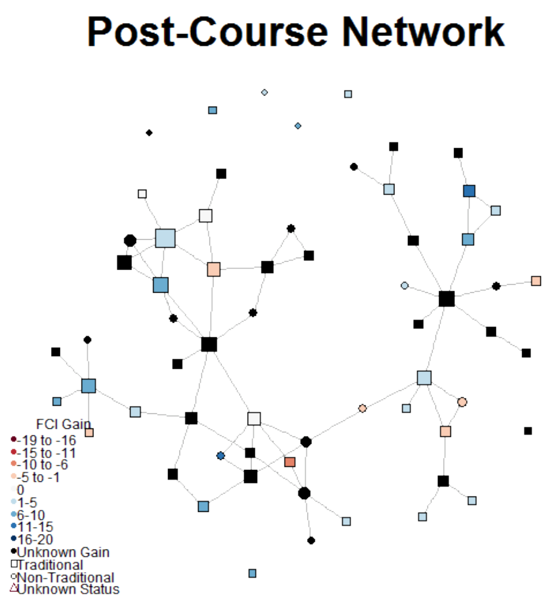


Figure 4.34: The post-course network is colored by FCI score gain values, sized by post-course degree centrality values, and shaped by student non-traditional/traditional status. There are 63 nodes with FCI gain values for 35 of them. The central network object is held together by only one node: a non-traditional student who lost conceptual knowledge throughout the course.

Log-Linear Plots

Log-Linear Degree Plots Figure 4.35 implies that very minimal degree gain occurred. Students tend to maintain their number of student connections from pre- to post-course. Non-traditional students have lower degree distributions than traditional students.

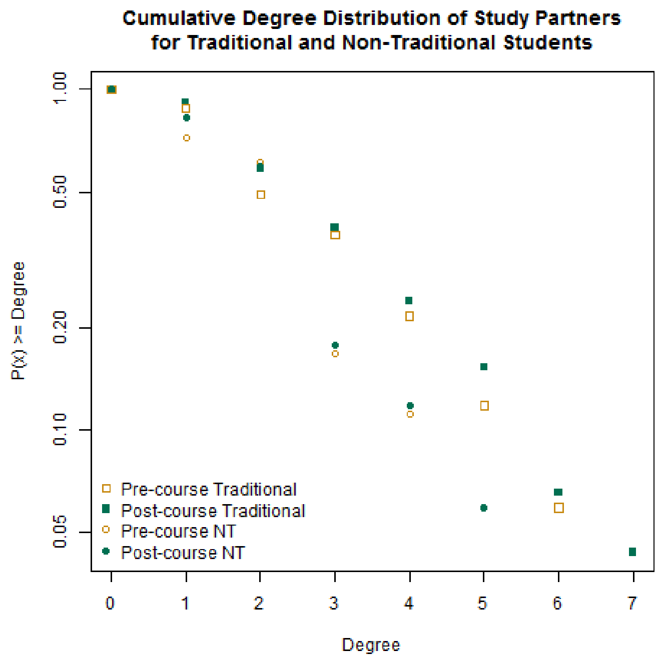


Figure 4.35: Almost no degree gain is shown for either student type. Non-traditional students have lower degree values. (Pre-course: NT=41, Trad = 161. Post-course: NT=30, Trad = 144.)

Log-Linear Betweenness Plots Figure 4.36 meets expectations as the post-course values reflect the anticipated high betweenness values for those students that connect the smaller networks together. Looking at the betweenness values of the other students, we see linear shapes with definite post-course gain, unlike the lack of degree gain depicted in Figure 4.35.

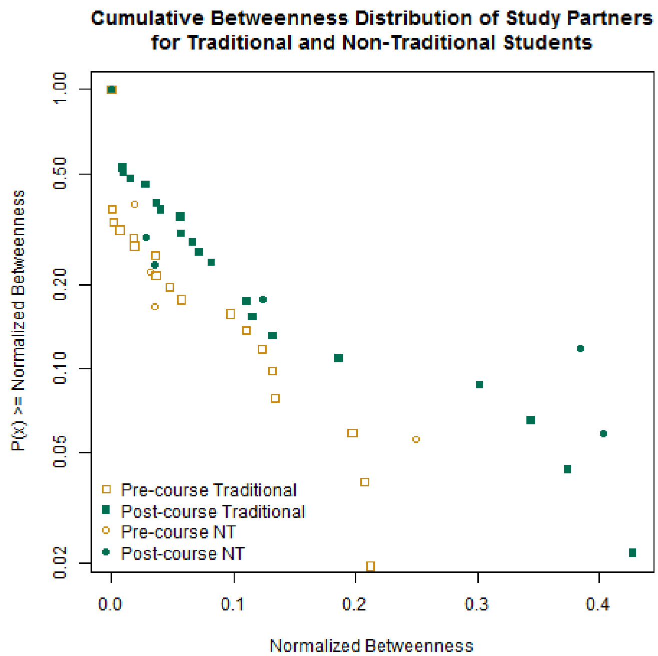


Figure 4.36: A definitive gain in betweenness is shown from pre- to post-course for traditional students. Several students (6) have high post-course values because they are the only connections from smaller subnetworks to other subnetworks as shown in Figure 4.34.

Log-Linear Closeness Plots Figure 4.37 shows that even though non-traditional students began the course with lower pre-course values, they have increased their closeness centrality to match that of traditional students. This is interesting since the degree values of students did not change much throughout the class, so the students' connections have changed in some way that makes them less isolated, but without additional study partners.

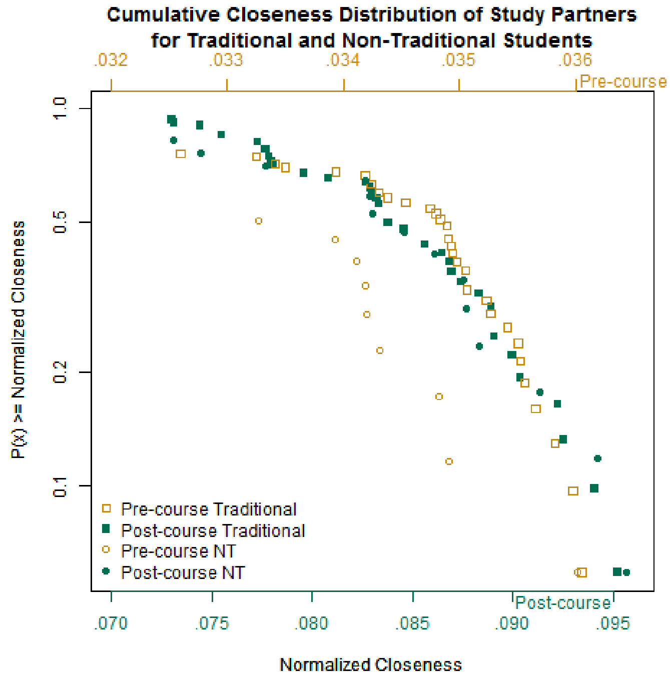


Figure 4.37: Closeness is plotted by pre- and post-course and subsetted data. Non-traditional students have lower pre-course values, but end with comparable post-course values, increasing their closeness centrality.

Log-Linear PageRank Plots The plot, shown in Appendix B, has a similar form as Figure 4.23 for Dataset B. The difference between the groups grows over the duration of the class leaving non-traditional students with definitively lower PageRank than that of traditional students. They started the pre-course with slightly lower values, but that separation has grown throughout the class. In other words, the connections that non-traditional students have at the end of the course are less connected and/or less exclusive (those study partners are studying with several other people and are less important) than the connections that traditional students made. The post-course traditional students form a linear plot indicating a logarithmic relationship.

Tables of Network Statistics

See Appendix B for mean and standard error values for the combined dataset. No t-tests revealed significant values for values of centrality of non-traditional and traditional students, so they are not reported.

4.5.3 FCI Statistics and Diagrams

Alluvial Diagram

Figure 4.38 shows how non-traditional came into the class with a higher amount of conceptual knowledge and appear to have maintained or improved upon that knowledge. Traditional students have some losses, but mostly gains in conceptual understanding. Comparing the bin sizes from pre- to post-course, it is evident that the class gained conceptual knowledge as anticipated.

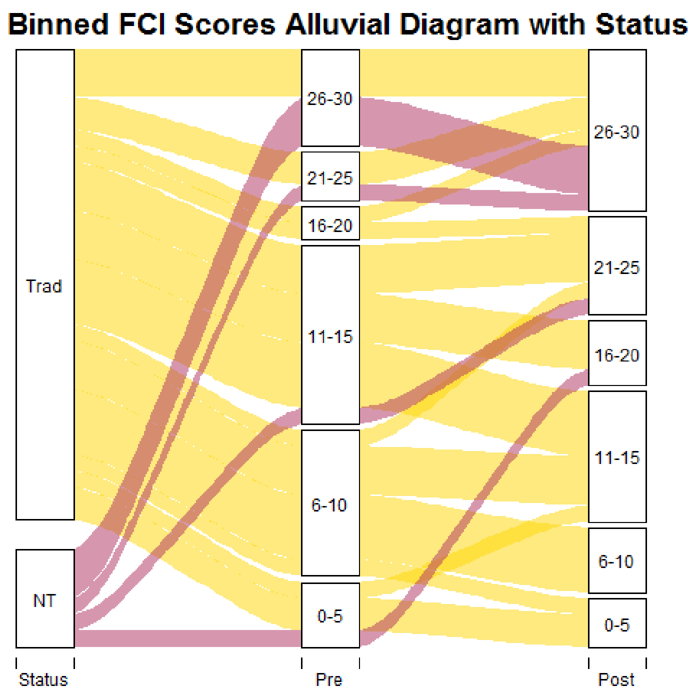


Figure 4.38: Alluvial diagram shows overall conceptual learning appears as there are smaller sized low FCI score bins in the post-course columns. A large portion of the non-traditional students had a high pre-course FCI score (and retained that score).

FCI Statistics

Basic statistics for the FCI pre- and post-course and gains and completed t-tests on subsetted data are reported in Appendix B. T-tests were completed on pre-course, post-course and conceptual gain values between non-traditional and traditional subsetted data. Results with $p < 0.05$ are reported.

Post-course FCI scores had $p=0.0271$ between traditional and non-traditional students.

Cohen's d was calculated for the post-course FCI data with *d=.786* which corresponds to a large effect size with non-traditional students ending the course with more conceptual knowledge. Without each subset consisting of 26 or more datapoints, it cannot be definitively stated that a different effect size was missed. (There are 36 traditional and 6 non-traditional datapoints.)

4.5.4 FCI and Network Data Combined

Pearson Correlation Tests on FCI and Degree Centrality

Correlations between FCI scores and gain and degree centrality are provided in Table 4.20. There are three sets of bolded values where $p<.05$. All have correlation values that (with 66 datapoints in each set) would be a medium effect size. The traditional subset FCI pre-score and post-course degree value says that if a traditional student entered the class with a higher level of conceptual knowledge, they had less post-course study partners. This is also true for the whole class dataset. The whole class dataset also has a negative correlation for post-course FCI and degree which was unanticipated by previous research, but similar to the result from Dataset A.

		FCI Pre-Course		FCI Post-Course		FCI Gain	
		All Data					
		r	p-value	r	p-value	r	p-value
All Data	Pre Degree	-0.0520	0.0703	-0.0740	0.635	-0.00064	0.998
	Post Degree	**-0.318**	**0.024**	**-0.352**	**0.025**	-0.0915	0.623
		Non-Traditional Data					
		FCI Pre-Course		FCI Post-Course		FCI Gain	
		r	p-value	r	p-value	r	p-value
Non-Traditional	Pre Degree	-0.353	0.218	-0.396	0.295	-0.447	-
	Post Degree	-0.0935	0.775	- .275	0.484	-0.270	-
		Traditional Data					
		FCI Pre-Course		FCI Post-Course		FCI Gain	
		r	p-value	r	p-value	r	p-value
Traditional	Pre Degree	0.0583	0.724	0.0452	0.796	0.0877	0.647
	Post Degree	**-0.423**	**0.0096**	-0.0300	0.0903	-0.0305	0.881

Table 4.20: Pearson Data Correlations For Degree and FCI values for full data and subsetted data. Note bolded p-values are less than .05.

FCI and Network Statistics

Statistics for the dataset of students with FCI and network information are shown in Appendix B.

4.6 Results Summary

Table 4.21 summarizes the results for each dataset.

Table 4.21: Summary of FCI and SNA results with non-traditional students' values compared to traditional students' values and traditional students' values compared to non-traditional students' values. Statistically significant differences are **bolded**.

Dataset	Student Type	Timing	FCI Trends	Centrality Trends (NT/Trad compared to Trad/NT) Degree	Betweenness	Closeness	PageRank
A	NT	Pre	lower	**lower**	lower	lower	lower
		Post	lower	same	no trend	lower	higher
		Gain	higher	higher	-	-	-
	Trad	Pre	higher	**higher**	higher	higher	higher
		Post	higher	same	no trend	higher	lower
		Gain	lower	lower	-	-	-
B	NT	Pre	-	**lower**	lower	lower	lower
		Post	-	**lower**	lower	lower	much lower
		Gain	-	loss	-	-	-
	Trad	Pre	-	**higher**	higher	higher	higher
		Post	-	**higher**	higher	higher	much higher
		Gain	-	gain	-	-	-
C	NT	Pre	lower	same	lower	same	same
		Post	same	lower	much lower	lower	lower

Table 4.21: Summary of FCI and SNA results with non-traditional students' values compared to traditional students' values and traditional students' values compared to non-traditional students' values. Statistically significant differences are **bolded**.

Dataset	Student Type	Timing	FCI Trends	Centrality Trends (NT/Trad compared to Trad/NT)			
				Degree	Betweenness	Closeness	PageRank
		Gain	loss	lower	-	-	-
		Pre	higher	same	higher	same	same
	Trad	Post	same	higher	much higher	higher	higher
		Gain	same	higher	-	-	-
D	NT	Pre	higher	-	-	-	-
		Post	higher	-	-	-	-
		Gain	higher	-	-	-	-
	Trad	Pre	lower	-	-	-	-
		Post	lower	-	-	-	-
		Gain	lower	-	-	-	-
E	NT	Pre	same	lower	no trend	lower	no trend
		Post	**higher**	lower	no trend	same	lower
		Gain	higher	none	-	-	-
	Trad	Pre	same	higher	no trend	higher	no trend

Table 4.21: Summary of FCI and SNA results with non-traditional students' values compared to traditional students' values and traditional students' values compared to non-traditional students' values. Statistically significant differences are **bolded**.

Dataset	Student Type	Timing	FCI Trends	Centrality Trends (NT/Trad compared to Trad/NT) Degree	Betweenness	Closeness	PageRank
		Post	**lower**	higher	no trend	same	higher
		Gain	lower	higher	-	-	-
F	NT	Pre	lower	lower	**none**	lower	lower
		Post	lower	lower	none	much lower	lower
		Gain	same	loss	-	-	-
	Trad	Pre	higher	higher	**higher**	higher	higher
		Post	higher	higher	higher	much higher	higher
		Gain	same	greater loss	-	-	-
G	NT	Pre	lower	lower	lower	much lower	no trend
		Post	much higher	higher	no trend	no trend	higher
		Gain	lower	greater loss	-	-	-
	Trad	Pre	higher	higher	higher	much higher	no trend
		Post	much lower	lower	no trend	no trend	lower
		Gain	higher	loss	-	-	-

Chapter 5

Discussion

Due to this study's various class structures, populations, and instructors, broad conclusions are difficult to make, but observed trends are discussed with respect to similarly structured and sized classes. Network data is particularly difficult to compare due to the massive number of factors that influence the network. This is exacerbated by the different classroom structures, sizes, and instructors. SNA in PER has few results currently, so limited research exists to confirm if these results are the norm. Given the lack of well-established results, primarily exploratory studies are useful.

5.1 Networks

5.1.1 Degree Centrality Values

Across all datasets presented, non-traditional students enter the class with lower degree centrality. This is not significant in all sections, but is in Datasets A and C. At the start of the course, these students have smaller study networks and fewer peers with whom to learn physics. Another interesting observation about the average pre-course degree values is that they are all centered around 2 study partners. Class sizes here widely varied: from 24 to 203 students, yet the average pre-course degree values never reach 4 for any subset. This is quite peculiar as it was anticipated that large lectures would have higher pre-course degree values because there are more peers for a student to potentially work with. Since this class is typically taken students' second semesters (due to the pre-requisite calculus requirement), it's possible that students have already made a few friends and know who they study well with.

Again, despite the large class sizes, post-course degree values never reach an average of 4 for any subset. It was anticipated (especially for large classes where active-learning and peer-cooperation was facilitated) that post-course values would be significantly higher as students would constantly be working together in the course. With the exception of the Dataset A, non-traditional students tend to end the course with less study partners as well. Because this occurred across traditional lecture halls and SCALE-UP classrooms and large and small sections, it seems that the instructional methods do not encourage non-traditional students to become as social about physics in the classroom. Only in one section (Dataset B) is there a significant difference between post-course degree values for traditional and non-traditional students. This is the result of lower pre-course degree values of non-traditional students which did not increase in the post-course and slight increases in traditional students' pre- to post-course degree values. The lack of change in non-traditional students pre- to post-course degree and slight growth for traditional students from pre- to post-course suggests that the course structure was not conducive to socialization in the learning process. Stagnant or minimal growth was anticipated as the course instructor did not use any group solving or peer-cooperation encouragement teaching methods.

Large lectures in auditorium-style lecture halls showed an increase in degree and a more comprehensively connected network, unlike Brewe's [8] results which said large lectures tend to have stagnant connections. Additionally, the pre-course networks analyzed here show a substantial number of students connected which were different from Brewe's results. Dataset E is the only large class with a SCALE-UP classroom. The network was more connected in the post-course, but had many smaller subnetworks that were loosely linked together as shown in Figure 4.34. This result is not repeated in other active-learning environments, possibly due to the low n values, but it is posited that this is due to the seating arrangements. Since the average degree value is 2.22, most students named two students as study partners. They were assigned groups (which were switched mid-course) of 3 students to work with, so it can be inferred that they likely named their group members and potentially another friend or member of a previous group. Information on group assignments is available to determine if this played a role at a future time.

Because the sample sizes for non-traditional students are minimal for the Datasets F and G, limited discussion will occur. Traditional students in the early morning class entered with 2.5 study partners and in the mid-morning class (G) had 3.5 study partners which may be due to the smaller sample size or could be the result of students being more active and social by mid-morning. Regardless of what pre-course value they had, they exited the course with only 2 study partners, despite sitting at tables with 4 seats. It is possible that only 3 students sat at each group and this could explain the difference, but classroom observations would have to accompany the research to support that claim. Alternatively, there may be key people (who didn't take the survey) missing from the dataset. With low n values, missing a couple of students could distort the network.

5.1.2 Other Centrality Values

While degree values were the most analyzed and compared centrality measure in this study, other centrality measures were calculated to determine if any additional information or trends could be revealed.

Betweenness

It was initially thought that since non-traditional students have fewer incoming connections, they would likely have lower betweenness values as there are fewer links for information to be shared (or transferred) from one node, through the non-traditional student, and reaching another node. In all presented sections, this manner of thinking is accurate: non-traditional students have lower pre-course betweenness values. Several sections maintained a lower betweenness value, while Datasets A and E had comparable post-course betweenness values for both types of students and Dataset G had higher betweenness values for non-traditional students.Dataset A, once again, shows the non-traditional students making up the pre-course difference and ending the class with identical post-course betweenness values. This result is seen again in Dataset E: non-traditional students make up much of the pre-course difference to end the class with comparable post-course betweenness. Dataset G's non-traditional students actually increased their betweenness values at the post-course to surpass those values for traditional students. All other datasets show non-traditional students having lower post-course betweenness values than those of traditional students.

Since the large, interactive engagement classrooms (like those of Dataset A and E) show comparable post-course results, it may be concluded that these classes have encouraged non-traditional students to become a physics concept messenger, just like their traditional peers. Traditional large lectures and the smaller group settings do not seem to have this end result. Non-traditional students end the class with lower betweenness values and do not appear to have as much betweenness. This is also supported by having lower degree values for the same reasoning as pre-course betweenness values being lower, as discussed at the beginning of this section.

Closeness

Anticipated results for this centrality measure follow the same reasoning as betweenness: non-traditional students will have lower closeness values because they will have less study partners and be farther from the inner-workings of the network (especially those isolated students). While it seems that this logic holds for many of the sections, in Dataset A pre-course closeness values are about the same. This could be part of the explanation for why Dataset A's post-course values tend to be the same. If non-traditional students are not particularly farther away from the inner workings on the network, they may be more likely to become more integrated into the concept sharing operation. This would explain why they compensate for the pre-course differences and end the class on equal centrality footings with traditional students. Similarly to betweenness values, many of the classes show the same amount of growth for traditional and non-traditional with non-traditional students finishing closer to the outskirts of the network. After seeing the degree results, this was anticipated for the same reasoning as listed above.

PageRank

PageRank centrality was included as a trial to see if any additional results could be concluded from its trends. Due to the undirected nature of the network, much of the PageRank information is altered, so it holds less meaning. Conceptually, it was anticipated to have similar trends to closeness. Regardless of how many connections a student has, if those connections are well-connected/important, the student's PageRank will be higher. So if the student's connections are well-connected, they are likely closer to the inner-workings of the network. It appears that this is not necessarily the case, as PageRank changes do not show the same trends of growth. Tables 4.3, 4.4, 4.5, and 4.6 show that PageRank was the least correlated centrality measure. In fact, they do not even show trends when compared to each other. For Dataset A, where both student types ended the course with comparable values, despite the difference in pre-course values, non-traditional students actually increase their PageRank so much that they finish ahead of traditional students. Increases are seen in Dataset E, where the network actually fractured, and Dataset B shows non-traditional students losing PageRank, while traditional students gain PageRank. Due to the variety of results for this centrality type, it does not appear to hold much information about how the network has really changed. This may be due to forcing the network to be undirected. It would be worth attempting another analysis of this centrality with a directed network to see what results would be found.

5.1.3 Dataset A

This section presented a unique result where non-traditional students entered the course with a lower number of study partners, but matched the post-course values of traditional students. However, betweenness and closeness values show the same amount of gain with non-traditional students having lower values in both. PageRank shows a different growth where traditional students have minimal gain, but non-traditional students, who started with lower PageRank values, end with higher PageRank values. These results imply that while non-traditional students made more connections, they are still closer to the outskirts of the post-network than traditional students (where betweenness and closeness values are low). The PageRank values imply that traditional students' connections are not as well-connected and special as those of non-traditional students. So while traditional students are more between and closer to the center of the network, their connections are not as important as those of non-traditional students in the post-course.

5.2 FCI

5.2.1 Full Class Comparisons

Pre-course FCI scores for most groups range between ten and twelve, which means that students tend to come in with similar levels of conceptual understanding. Post-course scores show a variety of different values. It was expected that the smaller sized datasets would show more gain than the larger classes due to the ability to get more personalized instruction. This is true for Datasets F and G, but not for Dataset C. The small datasets (F and G) showed larger gain than all other sections which may reflect the instructor's ability to effectively teach the force concepts tested on the FCI. Average score gains for these sections were 10 and 8, respectively. (Average gain was near 5 for the other sections.)

Previous research says that courses with interactive engagement teaching strategies (peer-cooperation, group problem solving, etc.) have higher conceptual gains on the FCI [21]. This is seen here with Datasets F and G, where the instructor used group problem solving in the classroom, but class size may have had an effect as well.

5.2.2 Non-traditional/Traditional Comparisons

The only statistically significant result when comparing FCI scores for traditional and non-traditional students was found in Dataset E. This found that non-traditional students tended to score higher on the post-course FCI than traditional students did in a moderate-sized SCALE-UP classroom. This may be influenced by the small n value (6 non-traditional datapoints).

Although not a significant result, non-traditional students tended to have higher conceptual gains than traditional students in the larger lecture sections (Datasets A, D, and E).

This may be a subsequent result of the changing teaching methods in secondary education since non-traditional students have completed their secondary education. Secondary education now implements active-learning and peer-cooperation instructions more frequently than it did in the previous decade. Younger students, who went to high school in more recent years, may have struggled to learn as effectively in a traditional, large-scale classroom since they were likely to have been educated in more active-learning based classrooms. Non-traditional students, who likely learned from traditional lectures in high school, fared better in large classes where it is more difficult to get one-on-one instruction from the professor. In the smaller classes with active learning environments, non-traditional students tend to have conceptual gains comparable to or less than those of traditional students. This also supports non-traditional students' struggles to transition from traditional learning environments to ones with active-learning. These results may have been insignificant due to the low n values of non-traditional students or they may not be at the level of statistical significance.

5.2.3 Centrality Ranking Correlations

When the centrality values were ordered by value and compared (via Kendall and Spearman permutation correlations), it was found that all p values were (essentially) zero. Correlation coefficient comparisons revealed that degree centrality (for Dataset A) correlated the best to the other types of centrality with Spearman values being consistently higher. This was also found to be true in (most) other datasets. The exception being betweenness having higher correlation coefficients (except with PageRank) than degree in Dataset G. With these results, it appears that degree centrality gives the most general information about the network and encompasses many similar trends of the other centrality types. All correlation coefficients were above 0.5, typically around 0.7-0.8.

5.3 FCI and Network

An overall goal of this study was to correlate network centrality with FCI scores and non-traditional student status. The hope was to find that students who were more central scored higher on the (post-course) FCI. A particular interest was to compare the subsetted data for non-traditional and traditional students. Correlations did not yield as many of these results as anticipated, but did show some trends. Dataset A showed that non-traditional and traditional students with lower incoming study partners had more pre-course conceptual knowledge. This result may be due to a large (traditional) international student population who had many internal ties at the pre-course, but limited conceptual knowledge or additional difficulty with a written test in a second language (to be analyzed in future work). Post-course values for traditional students revealed that lower post-course degree values were linked to higher FCI pre- and post-course scores. While post-course degree and pre-course FCI score correlations were not the aim of this study, it is an interesting note that may be able to be used as a predictor. Do traditional students with higher incoming FCI pre-course scores network with fewer students because they do not necessarily "need to study?" Dataset E also showed the link between traditional students and FCI pre-course scores with post-course degree. This was again a negative relationship, so higher FCI pre scores were linked to lower post-course degree centrality.

While previous research [20] [10] predicted links between higher centrality and more conceptual learning, that cannot be verified with these results. Limited significant findings exist in this data and do not conclude that higher centrality (in any particular measure) was linked to higher gains or scores on the FCI.

5.4 Research Objective Addressed

Significant results do not show a particular difference in non-traditional and traditional students' FCI and network values. Individually, we see that non-traditional students tend to fare better (in learning conceptual knowledge) in large lecture classes than traditional students, but struggle in smaller intimate courses. Centrality values (with the exception of Dataset A) show non-traditional students lagging behind traditional students at pre- and post-course values. Without more similarly structured and sized classes, it is difficult to determine which centrality values gives the best picture of the network. It is this researcher's opinion that betweenness and degree are the most telling centrality measures for an undirected network. Future work can be done for comparable classes of this course, as well as analyzing PageRank centrality with a directed version of the network. Consideration for the large international student base could also play a role, particularly in pre-course network centrality. Additionally, some data had to be omitted due to low response rates; student incentives to take the surveys are needed in order to obtain enough data to give a whole class picture of the network.

Chapter 6

Conclusions

6.1 Concluding Remarks

No definitive findings were found regarding higher centrality values and more conceptual learning or knowledge. An unexpected result was found of high pre-course FCI scores in large sections correlating with lower post-course degree values in Datasets A and E. Non-traditional students tend to start and end the course (with the exception of Dataset A) with lower degree centrality values, but do increase their betweenness centrality. While closeness centrality increased, non-traditional students are still far farther from the inner workings of the network than traditional students. Dataset A provided the most significant results and showed an unrepeated trend of non-traditional students gaining more study partners to end the class with the same degree centrality as traditional students.

6.2 Future Work

This research leaves many opportunities for future analysis. Allowing the network to be directed could reveal important trends in PageRank and other centralities (degree, betweenness, and closeness). Students who identify others as connections, but are not identified by those others, provided additional information about how important they are to their connections. Directed networks require a high survey response rate, especially in small sections where the network statistics are sensitive to even a few missing nodes. Investigating the pre-course connections, especially for international students, could reveal how incoming connections exist and evolve throughout the course. Determining who students network with is also a potential plethora of study opportunities. For example, do non-traditional students only work with non-traditional students who may be more understanding of their lifestyle outside of class? Or does the opposite occur more frequently, where non-traditional students work with traditional students more often because traditional students are likely to have more time available to study?

Further studies could focus on how different class sizes and structures and instructional pedagogies affect conceptual gains and networking trends for traditional/non-traditional or other pairs of subgroups. These studies would require observations in the classroom and potentially interviews to detail the types of collaborations that took place inside and outside of class. SCALE-UP classes could include a parameter on group assignments, as well. Another opportunity for further work lies in the pre-course degree information. If all sections of data were combined (no instruction or instructor effects have occurred yet), pre-degree values could be compared to determine if there are any significant differences in the larger, comprehensive sample set.

Appendix A

Additional Datasets

A.1 Dataset F Results

While the course for this data set is identical, several traits are different from other datasets. This section was instructed in a small classroom meeting two days a week in the early morning for an hour and fifty minutes with an integrated recitation. The class size was capped at thirty students although the enrollment was not at capacity. The classroom had seating in groups of four to six. The instructor largely used cooperative group problem solving throughout his/her teaching.

Basic information about enrollment and survey response rates is provided in Table A.1. The low rate of post-course FCI was due to low attendance on the day the FCI was given in class.

		Pre-Course	Post-Course
Class Size		26	19
Response Rate	FCI	0.92	0.68
	Network Survey	0.69	0.84
	FCI and Network	0.81	0.63

Table A.1: Response rates for the data collected are shown. FCI rates are higher as it was proctored during the course, whereas the network survey was completed on students' personal time for the pre-course. At post-course many students were absent on the day the FCI was proctored.

A.1.1 Network Data

Table A.2 (printed in Appendix B) provides values of the number of nodes and edges and network density in the pre-course and post-course networks. From pre- to post-course node and edge values decrease. This is unexpected as it is anticipated that students will work together and make more connections when sitting at the same table as their peers.

		Pre-Course	Post-Course
Number of	Nodes	24	19
	Edges	32	19
Network Density		0.116	0.111

Table A.2: Number of nodes and edges (student identified connections) in Dataset F. Post-course has less nodes, as students have dropped the class and, interestingly, less connections per node. Network density values confirm a slightly lower proportion of potential edges were made.

A.1.2 Network Diagrams and Statistics

Figure A.1 is a network diagram for the pre-course network. It is a significantly smaller network (than Datasets A, B, D, and E) due to the smaller class size and a fair distribution of incoming conceptual knowledge. The pre-course network is more connected than what was anticipated with only one isolated student and all others connected in some way.

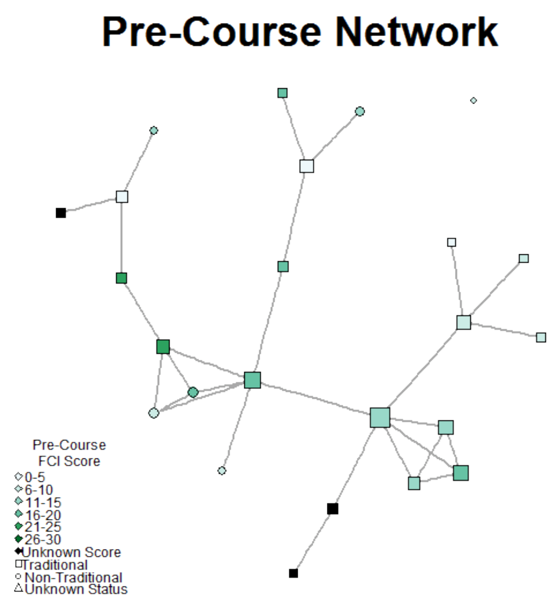


Figure A.1: The pre-course network is colored by FCI pre-course scores, sized by post-course degree centrality value, and shaped by student non-traditional/traditional status. There are 24 nodes with pre-course FCI scores for 21 of them. This is a well-connected pre-course network with only one student identified as an isolate.

Figure A.2 shows the post-course network for this dataset. It is less connected than the pre-course network in Figure A.1 and contains 3 isolates. Additionally, there is no longer one connected object. Two pairs of students are study partners independent from the rest of the connected class. This could be due to sitting at tables with the same students throughout the course and not having in-class contact with other students. It is positive to see that all shaded nodes are blue. This means that for all students who took the pre- and post-course FCI, the course improved their conceptual knowledge!

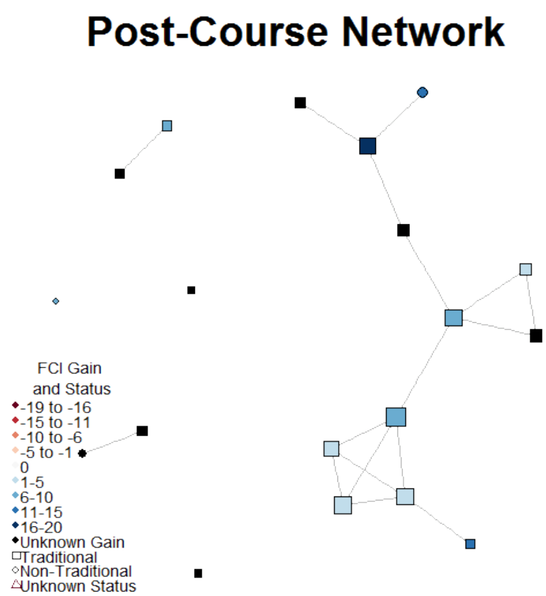


Figure A.2: The post-course network is colored by FCI score gain values, sized by post-course degree centrality values, and shaped by student non-traditional/traditional status. There are 19 nodes with FCI gain values for 9 of them. All gains are positive. The network is a bit segregated and contains a few isolates.

Log-Linear Plots

The previous dataset had each centrality's log-linear plots broken into each subset of data and displayed separately. This and subsequent datasets will only show the figures with subsetted plots superimposed.

It is important to be conscious of the lower N values in this dataset. In some places, non-traditional students in the post-course for example, there are only three data points.

Log-Linear Degree Plots Figure A.3 shows individual characteristics of traditional and non-traditional students cumulative degree distribution at the pre- and post-course. The linear shapes of the plots indicate a logarithmic relationship, but the small sample size limits the ability to draw conclusions. While it appears that non-traditional students have lower degree centrality, there are only 3 post-course data points in this dataset. (One student has a degree of 0, while the two others have a degree of 1.) Therefore, it is not reasonable to make generalizations.

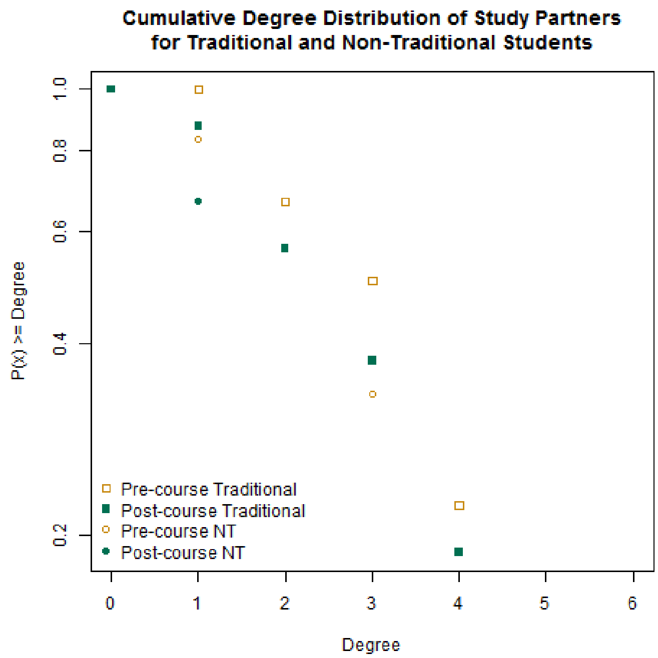


Figure A.3: The logarithmic cumulative degree of non-traditional and traditional students are superimposed to show their trends from pre- to post-course. The two groups appear to have comparable shapes with non-traditional students having slightly lower numbers of study partners. Note that small n values exist here. (Pre-course: NT=6 Trad =18. Post-course: NT=3 Trad=16.)

Log-Linear Betweenness Plots Figure A.4 shows the CBF for each student type. Again, due to low N values, non-traditional student generalizations are difficult. However, for traditional students, it is interesting that students tend to have less betweenness at the end of the course which would normally be indicative of a more connected network. However, Table A.2 indicates less connections per student and Figure A.1 shows that the network now has smaller connected groups/pairs rather than one main connected object.

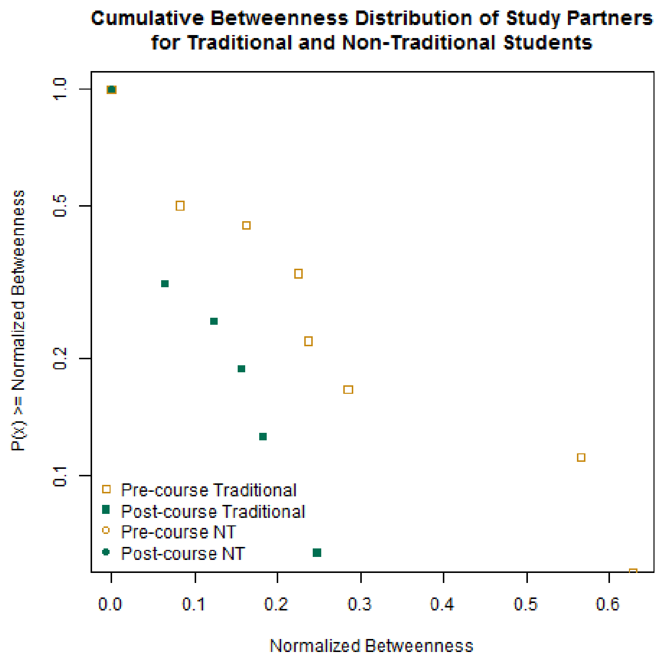


Figure A.4: Non-traditional and traditional student subsets are overlaid. All non-traditional points are stacked at the "0" betweenness entry. The pre-course betweenness of traditional students decreases by the end of the course.

Log-Linear Closeness Plots Figure A.5 shows the closeness distribution for traditional and non-traditional students at the pre- and post-course. Pre-course comparisons show that non-traditional students begin with lower closeness values. Traditional students appear to lose some of their pre-course closeness, which is consistent with degree and betweenness centrality.

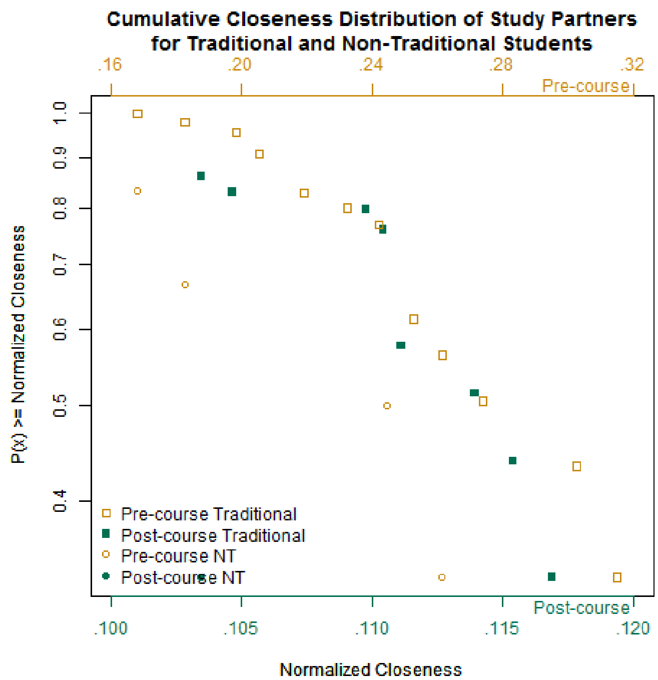


Figure A.5: Logarithmic-Linear Plot of Normalized Closeness for Non-Traditional and Traditional Students. Low level noise to discontinuity has been removed from the plot. Only one non-traditional student remains for post-course, so it will be ignored for this comparison. Traditional students appear to start with a higher closeness centrality, meaning they are fewer edges from the inner workings of network than non-traditional students.

Log-Linear PageRank Plots Figure A.6 shows the cumulative PageRank distribution at the pre- and post-course for each student type. There appears to be a general increase from pre- to post-course PageRank for both sets of data, which is interesting since degree and betweenness plots (Figures A.3 and A.4) showed a decrease. This is due to the post-network having several students with larger degree centrality and more direct contact from students with lower degree. The pre-network had two main nodes that had several long (think new node at each knuckle) fingertips connected. Now the tips of the fingers are connected directly with the "wrists." With low n values it cannot be definitively stated, but there appears to be a lower PageRank centrality for non-traditional students than traditional students.

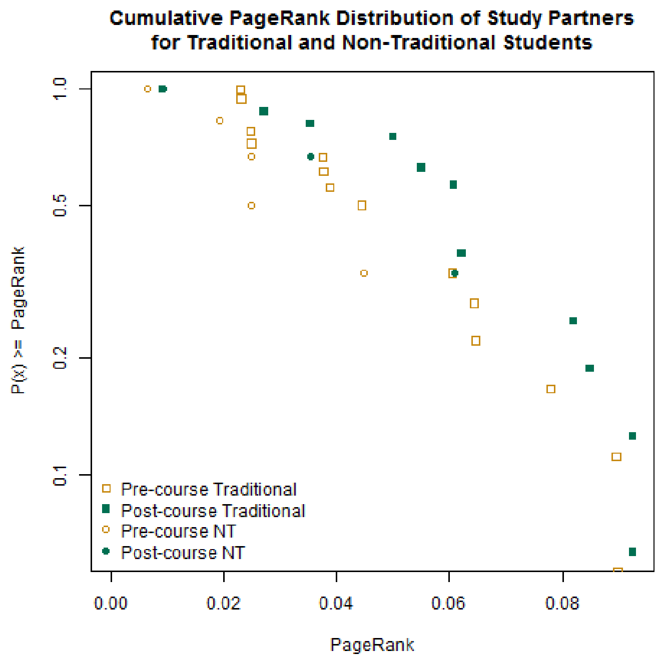


Figure A.6: The subsets of data are plotted together. It appears the non-traditional students tend to have a slightly lower PageRank than traditional students. Pre- to post-course trends show gains for both subsets. Unlike Figures A.3 and A.4, this plot shows a growth from pre- to post-course.

Alluvial Diagram

In Figure A.7 the reader can see how non-traditional and traditional students pre- and post-course degrees changed with the salmon color representing traditional students and green non-traditional students. Following the green non-traditional students, it can be seen that non-traditional students only have 1, if any, study partners at the end of the course. It is interesting that in a course with group seating at tables and cooperative problem solving that students rarely indicate high numbers of connections. This could be due to sitting with the same set of 2-3 peers.

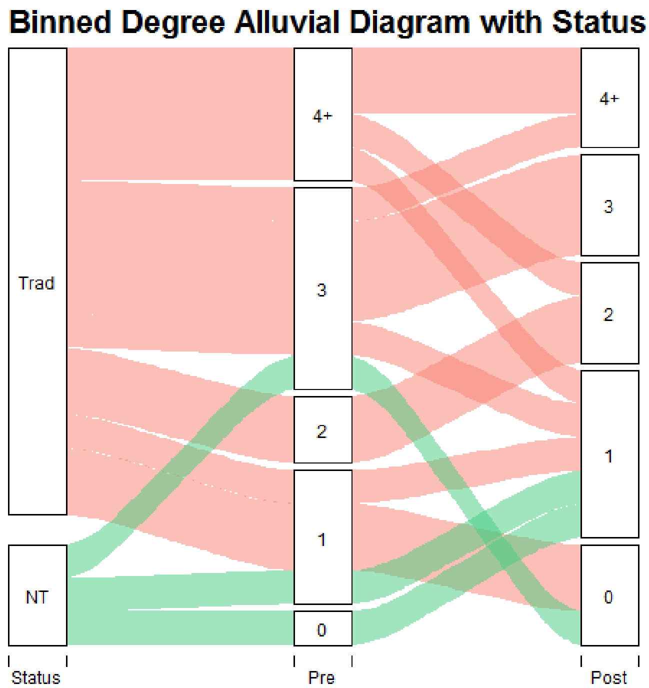


Figure A.7: Binned Alluvial Diagram for Pre- and Post-Course Degree with Status: shows the flow of non-traditional and traditional students' degree values from pre- to post-course. A gain in degree centrality was anticipated but does not seem to be reflected here.

Network Statistics and T-Tests

Full tables are printed in Appendix B.

T-tests were performed on the subsetted (by status) data and analyzed for unnormalized degree and (normalized) betweenness of the pre-course network. Only significant, $p<.05$, values are reported.

A t-test revealed a p-value less than .05 when testing pre-course betweenness values for non-traditional and traditional students. Cohen's d was calculated to determine the effect size: $d=.835$. This corresponds to a large effect size which would require 26 data points in each correlated subset to be conclusive. Since the whole class only has 24 data points, it cannot be conclusively said that this is a large effect size.

A.1.3 FCI Statistics and Diagrams

Alluvial Diagram

Figure A.8 shows the pre- to post-course transition for non-traditional and traditional students. It appears that all students gain conceptual knowledge and move into at least the next higher score bin. Because the data set is small (only 11 data points total: 2 non-traditional, 9 traditional), comparing the two data sets is inappropriate.

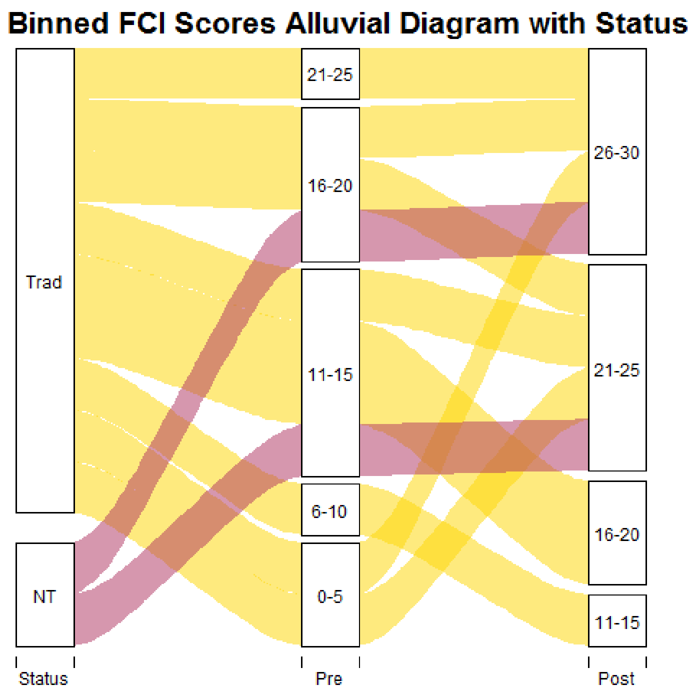
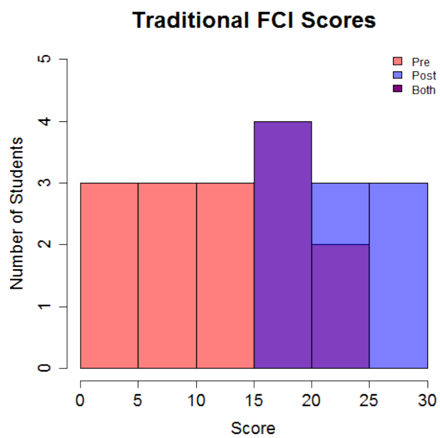


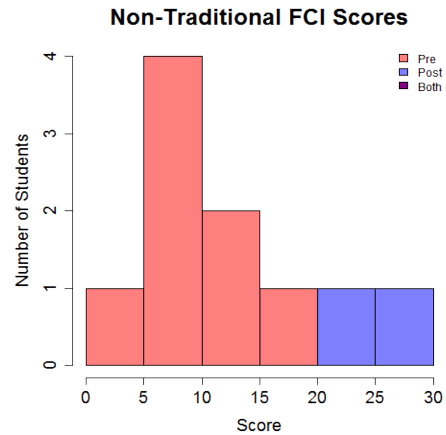
Figure A.8: Alluvial Diagram for Pre- and Post-Course FCI Scores with Status Binned. Overall, there are significantly smaller sized low FCI score bins in the post-course columns indicating an increase in conceptual understanding. Note: there are only 2 non-traditional (NT) data points.

Histograms

Figure A.9 suggests that non-traditional students seem to have had a higher proportion of students with large FCI gains than the traditional students did. This cannot be definitively said, as the n value is very small. Although the FCI post distribution also is shaped significantly differently for non-traditional students than traditional students, the shapes of each status-separated figure seem to stay somewhat consistent from pre- to post-course.



(a) Pre- and post-course FCI scores for traditional students. Students have gained, and the plot has a similar shaped from pre- to post-course. Note: low n values.



(b) Pre- and post-course FCI scores for non-traditional students. The post-course only contains 2 data points.

Figure A.9: Pre- and post-course FCI scores for each status are displayed.

Figure A.10 shows FCI gains ranging from 0 to 25 centered around approximately 9. Non-traditional students appear to be slightly above that value but with only 2 data points, that cannot be said conclusively due to the small sample size.

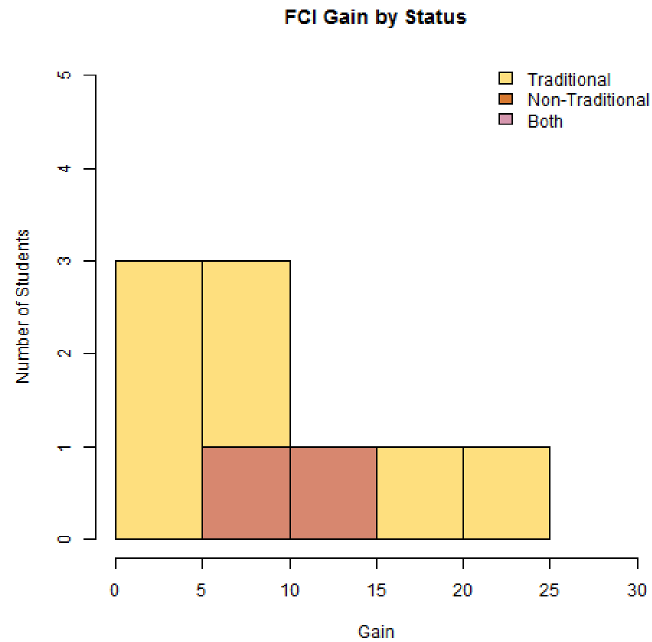


Figure A.10: A histogram of FCI gains colored by status and centered around a gain of approximately 9.

FCI Statistics

The sample sizes and basic statistical values for the pre- and post-course FCI as well as gains for both subsets and the entire class are in Table B.12. The mean values of FCI gain confirm that non-traditional students had a higher mean gain from Figure A.10 and give numerical values. Due to the small n values, no t-tests were performed. Full tables are in Appendix B.

A.1.4 FCI and Network Data Combined

Pearson Correlation Tests on FCI and Degree Centrality

There were no correlations in Table B.13 with p-values less than .05. Additionally, because the sample size is so small, some correlations could not be calculated. Similar negative trends from Dataset A are apparent here. Primarily those that say having more study partners has a negative effect on post-course FCI gain. These results are printed in Appendix B.

A.2 Dataset G Results

This course is instructionally and structurally identical to that of Dataset F. G's class was held immediately after Dataset F's class ended.

A.2.1 Network Data

Basic characteristics of the pre- and post-course networks are given in Table A.3. Some may wonder how the FCI and network response rate is higher than the network survey's individual rate. This data is compiled in a way that identifies how many nodes have FCI data, so it is possible that several students who took the FCI may have been named as study partners, but not actually taken the network survey themselves.

		Pre-Course	Post-Course
Class Size		30	26
Response Rate	FCI	1.00	.81
	Network Survey	0.70	0.69
	FCI and Network	0.97	0.77

Table A.3: Response rates for the data collected are shown. FCI rates are higher as it was proctored during the course, whereas the network survey was completed on students' personal time for the pre-course. For the post-course FCI many students were absent on the day the FCI was proctored.

Table A.4 provides values of the number of nodes and edges in the pre-course and post-course networks. From pre- to post-course node and edge values decrease more dramatically than node values do. This is unexpected as it is anticipated that students will work together with peers sitting at the same table.

A.2.2 Network Diagrams and Statistics

		Pre-Course	Post-Course
Number of	Nodes	29	23
	Edges	47	27
Network Density		0.116	0.107

Table A.4: Number of nodes and edges (student identified connections). Post-course has less nodes, as students have dropped the class and, interestingly again, less connections per node. The lower post-course network density value supports the posit of a less connected network.

Figure A.11 depicts a well-connected pre-course network with only one isolate. There are several nodes with high degree centrality values (all the same size).

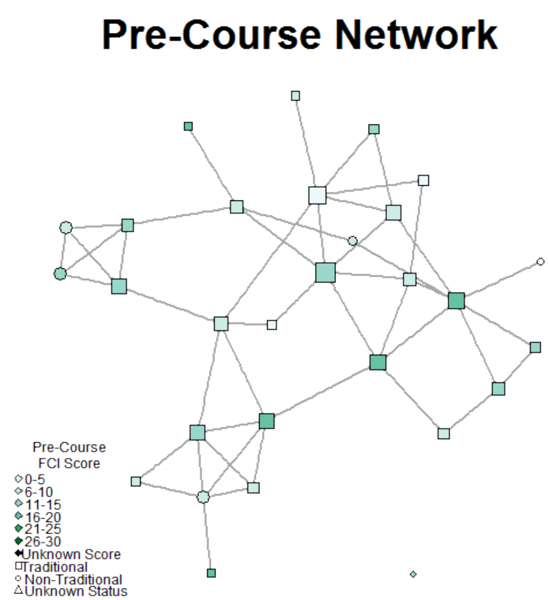


Figure A.11: The pre-course network is colored by FCI pre score values, sized by post-course degree centrality values, and shaped by student non-traditional/traditional status and shows a well-connected network with many nodes having high degree centrality (larger sizes). There are 29 nodes with pre-course FCI scores for all of them.

Figure A.12 shows the post course network which indicates the network has fractured as Dataset F also did. There are still a large amount of students with high degree values and all connected students with FCI pre- and post-course scores show a hue of blue indicating that they gained conceptual knowledge throughout the class.

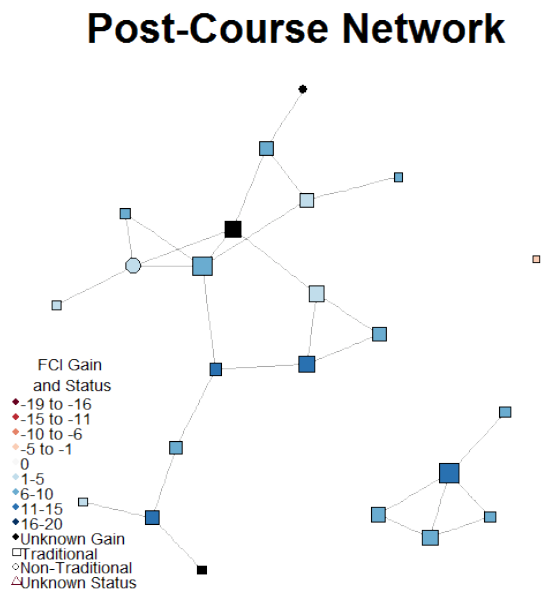


Figure A.12: The post-course network is colored by FCI score gain values, sized by post-course degree centrality values, and shaped by student non-traditional/traditional status. There are 23 nodes with FCI gain values for 20 of them. Only the isolated student lost conceptual knowledge.

Log-Linear Plots

Superimposed cumulative centrality distribution plots are below. It is important to be conscious of the lower n values in this dataset. In some places, non-traditional students, in the post-course for example, have only 2 data points.

Log-Linear Degree Plots The non-linear shapes of the plots in Figure A.13 are interesting. The small sample size limits the ability to draw conclusions, but it appears that students do not have a logarithmic relationship with their cumulative degree. This result is somewhat anticipated as Figures A.11 and A.12 had many nodes with (similarly sized) high degree values. A loss of degree centrality is indicated in this figure as well which was supported by the post-course network density value. While it appears that non-traditional students have lower degree centrality, there are only 6 pre-course and 2 post-course data points in this dataset. Therefore it is not reasonable to make generalizations.

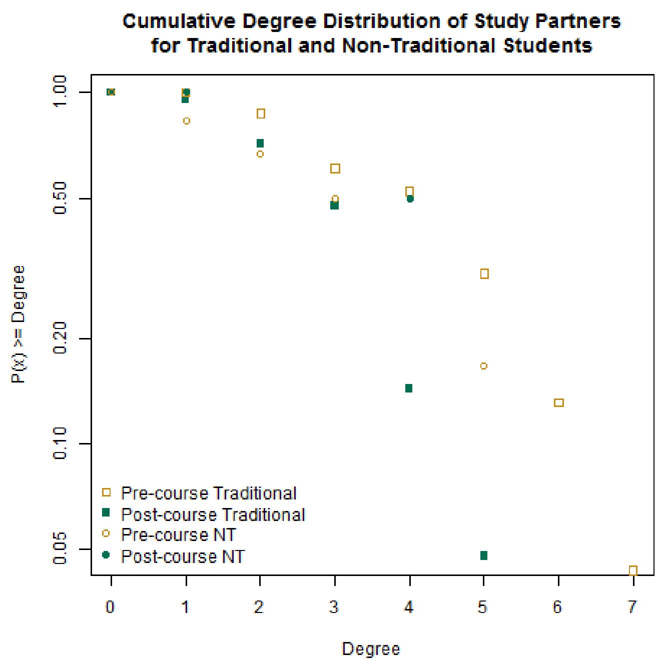


Figure A.13: The logarithmic cumulative degree of non-traditional and traditional students are superimposed to show their trends from pre- to post-course. The two groups appear to have comparable shapes with non-traditional students having slightly lower numbers of study partners at the start of the course. Note that small n values exist here. (Pre-course: NT = 6 Trad =23. Post-course: NT = 2 Trad =21.)

Log-Linear Betweenness Plots Figure A.14 shows that traditional students tend to have less betweenness at the end of the course, which could be indicative of a more connected network. However, since the post-course network object showed that the once connected network fractured, it is logical that betweenness centrality values have decreased. Again, due to low n values, non-traditional student generalizations are difficult. However TableA.4 indicates less connections per student.

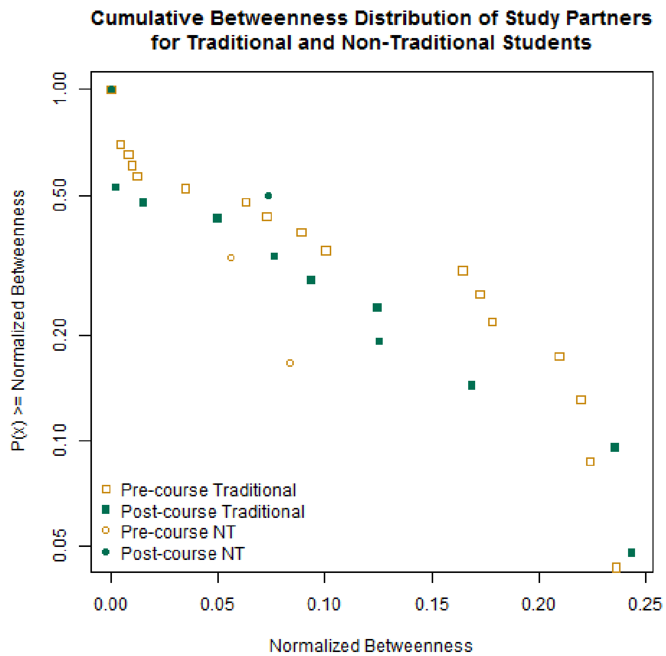


Figure A.14: Non-traditional and traditional student subsets are overlaid. All non-traditional points are stacked at the "0" betweenness entry. The pre-course betweenness of traditional students decreases by the end of the course.

Log-Linear Closeness Plots Figure A.15 shows the closeness distribution for traditional and non-traditional students at the pre- and post-course. Pre-course comparisons show that traditional students begin the class with higher closeness values and lose some of that closeness by the end of the course, which is consistent with degree and betweenness centrality. There are only 2 data points for post-course non-traditional students, so no conclusions will be drawn from them. This plot does appear more linear than the others, indicating a logarithmic decay in the proportion of the class with some closeness value.

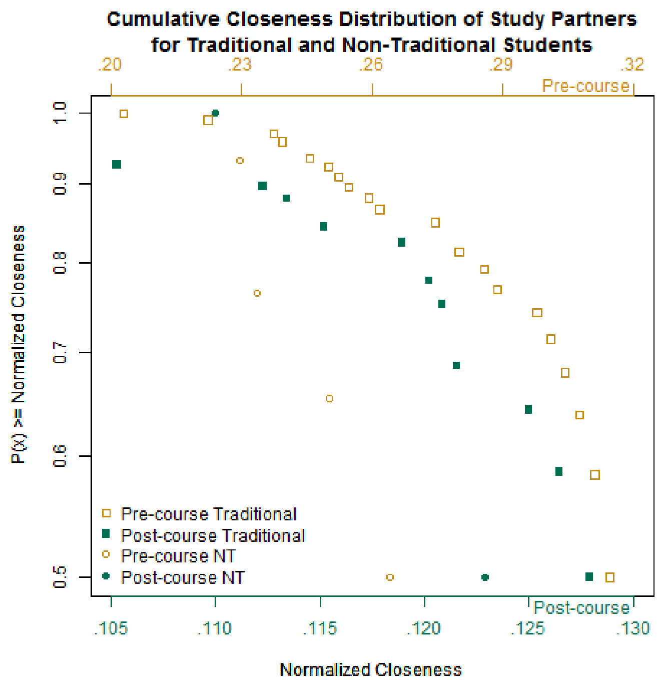


Figure A.15: Logarithmic-linear plot of normalized closeness for non-traditional and traditional students. Low level noise to discontinuity has been removed from the plot. Traditional students appear to start with a higher closeness centrality, meaning they are fewer edges from the inner workings of network than non-traditional students. By the end of the course, they have lost closeness.

Log-Linear PageRank Plots Figure A.16 shows a general increase from pre- to post-course PageRank for both sets of data. With low n values it cannot be definitively stated, but there appears to be a lower PageRank centrality for non-traditional students than traditional students. The shapes of the plots are slightly non-linear, but consistent for pre- to post-course traditional students.

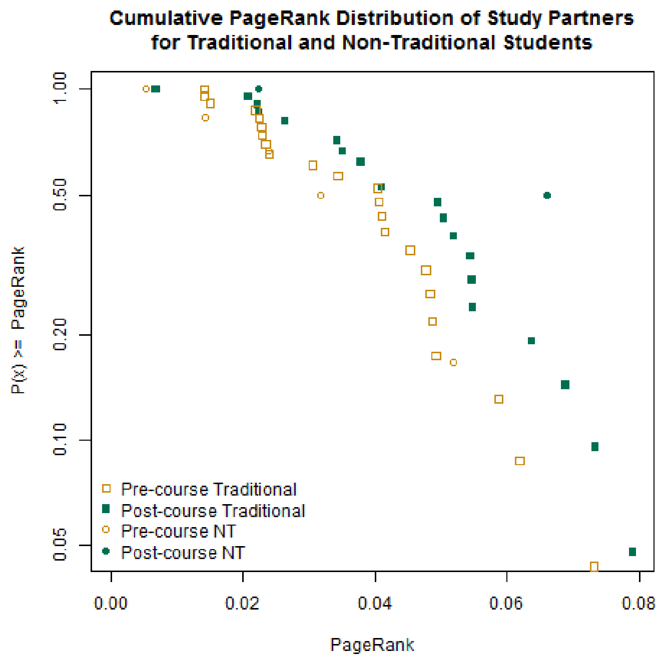


Figure A.16: The subsets of cumulative PageRank are plotted together. It appears the non-traditional students tend to have a slightly lower PageRank than traditional students. Pre- to post-course trends show gains for both subsets, but there are few data points for non-traditional students.

Alluvial Diagram

Figure A.17 shows a greater variety of degree centrality values than Dataset F, perhaps due to the later class time. A wide variety of changes in degree centrality values are shown here, thus no conclusions or generalizations can be made.

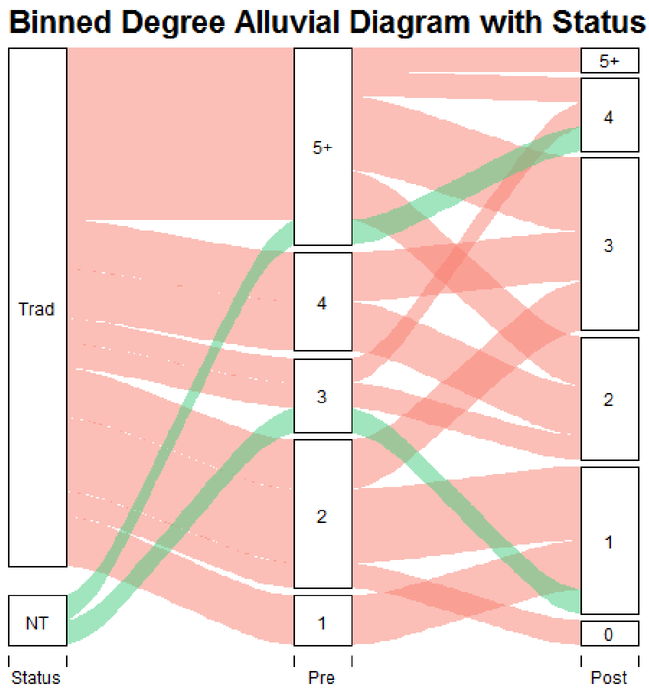


Figure A.17: Binned Alluvial Diagram for Pre- and Post-Course Degree with Status: shows the flow of non-traditional and traditional students' degree values from pre- to post-course. This diagram contains a variety of changes within the network making it difficult to draw conclusions.

Tables of Network Statistics

Tables are printed in Appendix B.

A.2.3 FCI Statistics and Diagrams

Alluvial Diagram

Figure A.18 shows that nearly all students gain conceptual knowledge and move into-at least-the next higher score bin.

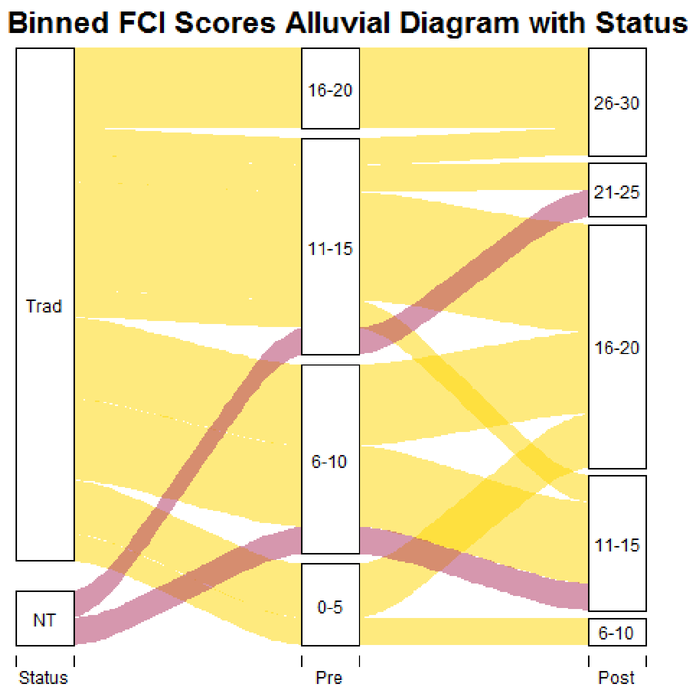
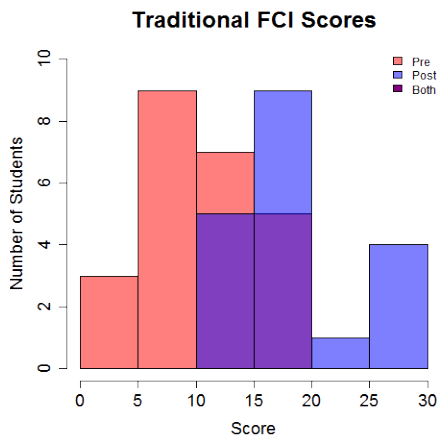


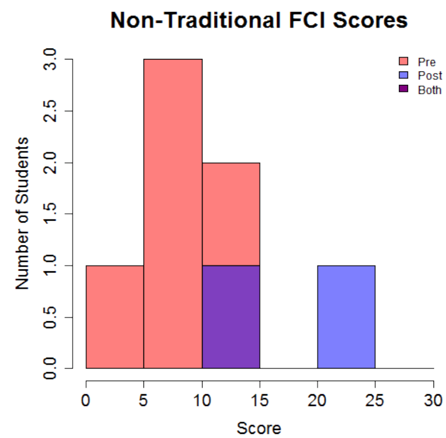
Figure A.18: Alluvial Diagram shows there are significantly smaller sized low FCI score bins in the post-course columns indicating an increase in conceptual understanding. Note: there are only 2 non-traditional (NT) data points.

Histograms

Comparing the traditional vs. non-traditional students pre- and post-course gains shown in Figure A.19 yields a definite rightward shift for traditional students. It also appears that the non-traditional students have a score gain, but with low n values, no reasonable conclusions can be drawn. The rightward shift suggests that after instruction students answer questions about force concepts more accurately. Pre-course graph shapes are very similar from traditional to non-traditional students, but due to low n values, but no reasonable conclusions can be drawn from the comparison of the post-course plots due to the low n values.



(a) Pre- and post-course FCI scores for traditional students. Students seem to have gained, and the plot has a similar shaped from pre- to post-course.



(b) Pre- and post-course FCI scores for non-traditional students. The post-course only contains 2 data points, but still has a rightward shift.

Figure A.19: Pre- and post-course FCI scores for each status are displayed.

While Figure A.20 is a loosely normally distributed plot for traditional students, there are a wide variety of FCI gain amounts shown. The mean gain for all students appears to be 8 with non-traditional students also straddling that value.

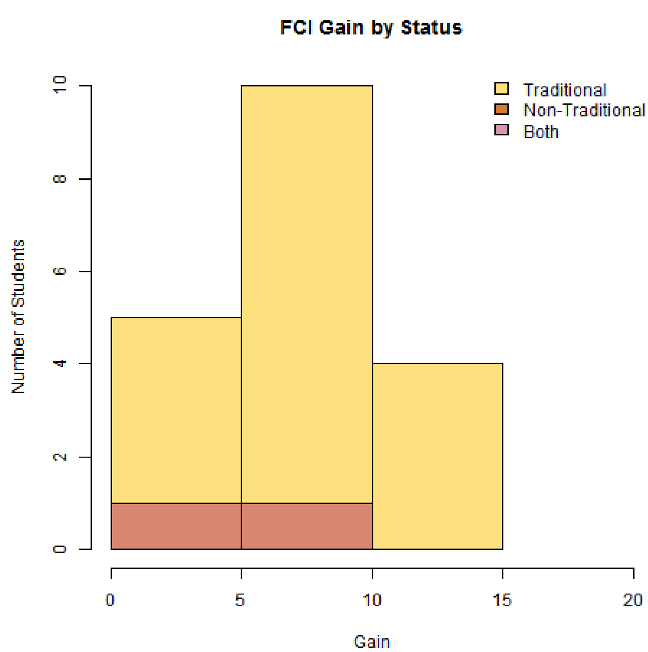


Figure A.20: A histogram depicting widely distributed FCI gains colored by status. Note: low n value for non-traditional gain.

FCI Statistics

The sample sizes and basic statistical values for the pre- and post-course FCI as well as gains for both subsets and the entire class are in Appendix B. Due to the small n values, no t-tests were performed, so there are no significant findings.

A.2.4 FCI and Network Data Combined

Pearson Correlation Tests on FCI and Degree Centrality

Since the non-traditional data set is so small, correlations are not reported. There were no correlations in Table B.17 with p-values less than .05. This class does not display the negative trends that Dataset A did. The positive correlations (though not significant) suggest that more study partners increased the level of conceptual knowledge. Additional information is printed in Appendix B.

Appendix B

Additional Figures and Tables

B.1 Dataset A

B.1.1 FCI and SNA means and standard error table

Dataset A's table of means and standard errors are shown below for the combined FCI and network dataset.

Table B.1: FCI and Network Statistics for Dataset A

(a) n values and FCI Statistics

	n values			FCI Pre-Course		FCI Post-Course		FCI Gain	
Type	Pre-Course	Post-Course	Gain	Mean	Standard Error of Mean	Mean	Standard Error of Mean	Mean	Standard Error of Mean
All	178	134	116	10.92	0.37	14.28	0.66	4.22	0.46
NT	36	22	17	10.15	0.68	13.1	1.3	4.9	1.1
Trad	144	99	112	11.10	0.43	14.52	0.74	4.10	0.50

(b) Degree Statistics

	Pre-Course Degree		Post-Course Degree		Degree Gain		Pre-Course Norm. Degree		Post-Course Norm. Degree	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	2.04	0.18	3.70	0.26	1.26	0.27	0.01010	0.00089	0.0214	0.0015
NT	1.44	0.31	4.32	0.77	2.53	0.84	0.0071	0.0016	0.0250	0.0044
Trad	2.18	0.21	3.48	0.27	1.04	0.27	0.0108	0.0010	0.0207	0.0016

(c) (Normalized) Betweenness, Closeness, and PageRank Statistics

	Pre-Course Betweenness		Post-Course Betweenness		Pre-Course Closeness		Post-Course Closeness		Pre-Course PageRank		Post-Course PageRank	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	0.00478	0.00082	0.0185	0.0021	0.00802	0.00021	0.0411	0.0010	0.00492	0.00030	0.00598	0.00031
NT	0.0027	0.0011	0.0215	0.0056	0.00712	0.00048	0.0433	0.0018	0.00441	0.00058	0.00683	0.00089
Trad	0.00526	0.00098	0.0179	0.0023	0.00823	0.00024	0.0407	0.0012	0.00504	0.00034	0.00582	0.00033

B.2 Dataset B

Figure B.1 shows the cumulative closeness plot for the subsetted data. Post-course closeness has increased, but non-traditional students are still much lower than traditional students.

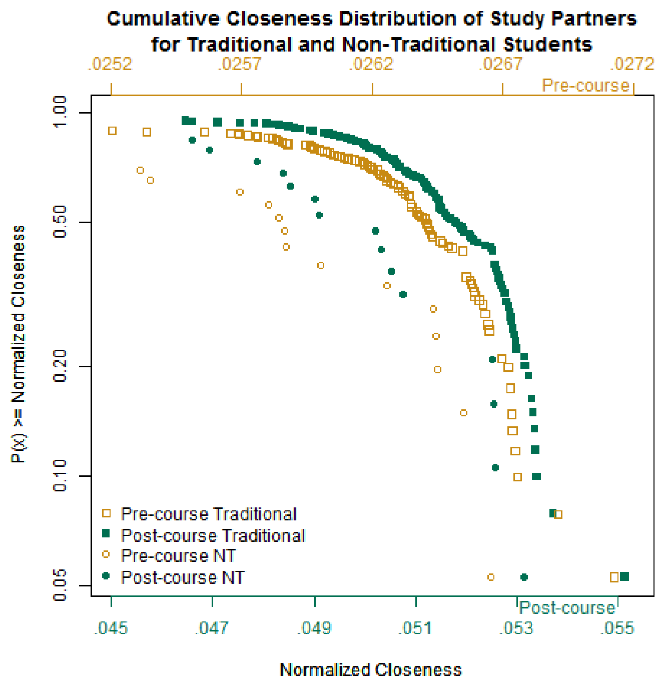


Figure B.1: A pre- to post-course closeness centrality gain is evident for both subsets. Non-traditional students have lower closeness values. The curved shape indicates a non-logarithmic relationship.

Basic statistic information is printed in Table B.2b for this dataset. T-tests revealed two significant results: pre-course degree and post-course degree between non-traditional and traditional students, which would be small and medium effect sizes, respectively, if there were enough data points.

Table B.2: SNA Statistics for Dataset B

(a) n values and Degree Statistics

	n values			Pre-Course Degree		Post-Course Degree		Degree Gain		Pre-Course Norm. Degree		Post-Course Norm. Degree	
Type	Pre-Course	Post-Course	Gain in Course	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	185	177	167	3.11	0.28	3.69	0.27	0.43	0.34	.0169	0.0016	.0210	0.0015
NT	22	19	19	1.77	0.37	1.68	0.27	-0.18	0.36	0.0096	0.0020	.0096	0.0015
Trad	163	157	148	3.29	0.32	3.96	0.29	0.50	0.38	0.0179	0.0017	0.0225	0.0017

(b) (Normalized) Betweenness, Closeness, and PageRank Statistics

	Pre-Course Betweenness		Post-Course Betweenness		Pre-Course Closeness		Post-Course Closeness		Pre-Course PageRank		Post-Course PageRank	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	0.0093	0.0023	0.0138	0.0031	0.02231	0.00060	0.04684	0.00099	0.00541	0.00041	0.00565	0.00033
NT	0.0041	0.0015	0.0046	0.0018	0.01950	0.00021	0.0430	0.0038	0.00391	0.00055	0.00355	0.00040
Trad	0.0100	0.0026	0.0150	0.0035	0.02269	0.00062	0.0473	0.0010	0.00561	0.00045	0.00592	0.00036

B.3 Dataset C

B.3.1 Network Data

Table B.3: SNA Statistics for Dataset C

(a) n values and Degree Statistics

	n values			Pre-Course Degree		Post-Course Degree		Degree Gain		Pre-Course Norm. Degree		Post-Course Norm. Degree	
Type	Pre-Course	Post-Course	Gain	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	28	29	24	2.00	0.26	3.24	0.42	1.29	0.58	0.0741	0.0097	0.116	0.015
NT	10	8	7	1.90	0.38	2.25	0.80	0.14	0.14	0.070	0.014	.080	0.028
Trad	18	21	17	2.06	0.36	3.62	0.48	1.76	0.70	0.0076	0.013	0.063	0.018

(b) (Normalized) Betweenness, Closeness, and PageRank Statistics

	Pre-Course Betweenness		Post-Course Betweenness		Pre-Course Closeness		Post-Course Closeness		Pre-Course PageRank		Post-Course PageRank	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	0.055	0.014	0.046	0.013	0.0855	0.0053	0.1704	0.0089	0.0357	0.0037	0.0344	0.0037
NT	0.042	0.020	0.022	0.016	0.0826	0.0097	0.146	0.024	0.0339	0.0053	0.0268	0.0065
Trad	0.063	0.018	0.056	0.016	0.0870	0.0065	0.1798	0.0076	0.0367	0.0050	0.0374	0.0044

No t-tests yielded p-values less than .05, so they are not reported.

B.3.2 FCI Data

FCI data is presented in Table B.4.

Table B.4: FCI Statistics for Dataset C

	n values			FCI Pre-Course		FCI Post-Course		FCI Gain	
Type	Pre-Course	Post-Course	Gain	Mean	Standard Error of Mean	Mean	Standard Error of Mean	Mean	Standard Error of Mean
All	25	17	13	8.24	0.66	12.4	1.3	3.3	1.5
NT	8	6	4	9.75	0.94	12.2	2.2	-0.5	3.3
Trad	17	11	9	7.53	0.83	12.5	1.7	5.0	1.3

B.3.3 Network and FCI Data

Table B.5: FCI and SNA Statistics for Dataset C

(a) n values and FCI Statistics

	n values			FCI Pre-Course		FCI Post-Course		FCI Gain	
Type	Pre-Course	Post-Course	Gain	Mean	Standard Error of Mean	Mean	Standard Error of Mean	Mean	Standard Error of Mean
All	24	17	12	8.21	0.69	11.9	1.4	2.8	1.5
NT	8	5	3	9.75	0.94	11.6	2.6	-3.7	1.3
Trad	16	12	9	7.44	0.88	12.1	1.6	5.0	1.3

(b) Degree Statistics

	Pre-Course Degree		Post-Course Degree		Degree Gain		Pre-Course Norm. Degree		Post-Course Norm. Degree	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	2.12	0.28	3.06	0.53	0.58	0.80	0.079	0.010	0.109	0.019
NT	1.75	0.45	2.20	1.24	-1.67	0.67	0.065	0.017	0.079	0.044
Trad	2.31	0.35	3.42	0.56	1.33	0.93	0.086	0.013	0.122	0.020

(c) (Normalized) Betweenness, Closeness, and PageRank Statistics

	Pre-Course Betweenness		Post-Course Betweenness		Pre-Course Closeness		Post-Course Closeness		Pre-Course PageRank		Post-Course PageRank	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	0.054	0.015	0.036	0.014	0.0882	0.0053	0.160	0.026	0.0375	0.0038	0.0331	0.0041
NT	0.021	0.019	0.026	0.026	0.078	0.012	0.124	0.037	0.0314	0.0060	0.028	0.010
Trad	0.070	0.020	0.044	0.017	0.0935	0.0053	0.174	0.013	0.0406	0.0048	0.0048	0.0042

T-tests results are reported in Table B.6. The full data set reveals significant results for post-course degree and FCI post-course score and gain. These are positive correlations, as anticipated, where higher post-course degrees indicate more conceptual knowledge (learned).

		All Data					
		FCI Pre-Course		FCI Post-Course		FCI Gain	
		r	p-value	*r*	p-value	*r*	p-value
All Data	Pre Degree	-0.347	0.093	-0.241	0.389	-0.103	0.74
	Post Degree	0.0299	0.892	**0.587**	**0.014**	**0.729**	**0.004**
		Non-Traditional Data					
		FCI Pre-Course		FCI Post-Course		FCI Gain	
		r	p-value	*r*	p-value	*r*	p-value
Non-Traditional	Pre Degree	0.0210	0.968	-0.053	0.917	-0.195	0.816
	Post Degree	0.0246	0.984	0.688	0.183	0.866	-
		Traditional Data					
		FCI Pre-Course		FCI Post-Course		FCI Gain	
		r	p-value	*r*	p-value	*r*	p-value
Traditional	Pre Degree	0.410	0.108	-0.350	0.361	-0.0768	0.845
	Post Degree	0.285	0.267	0.562	0.0597	0.541	0.103

Table B.6: Pearson Data Correlations For Degree and FCI values for full data and subsetted data. Note bolded p-values are less than .05.

B.4 Dataset D

Alluvial Diagram: FCI

Figure B.2 shows trends similar to those of Dataset A where non-traditional students are fairly well represented in all bins of FCI scores.

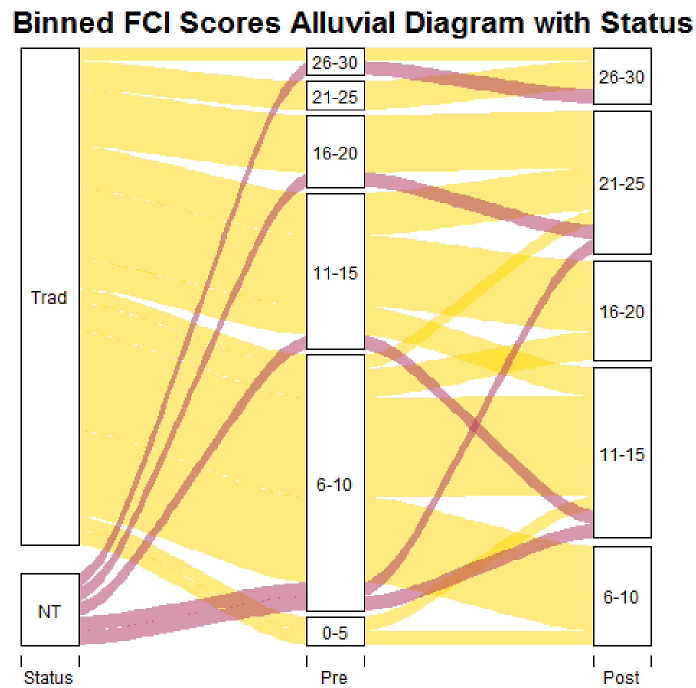
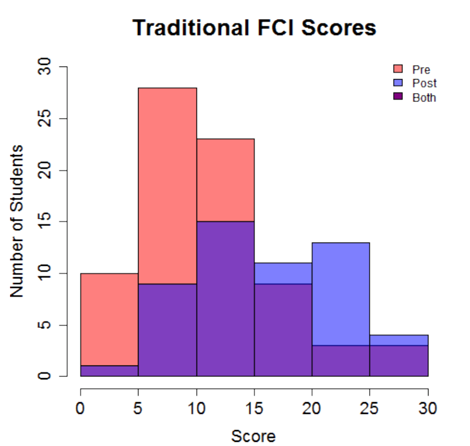
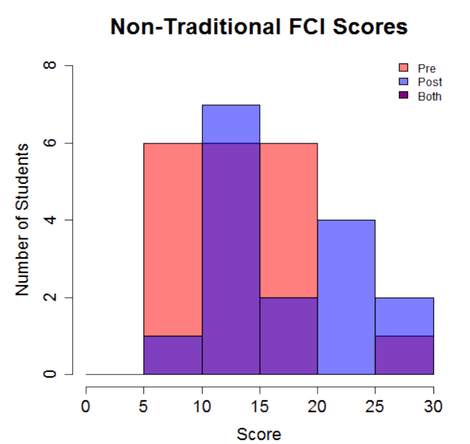


Figure B.2: Alluvial diagram indicates conceptual learning for all students as there are smaller sized low FCI score bins in the post-course columns.

FCI Histogram



(a) Pre- and post-course FCI scores for traditional students. Students have increased their scores, and the plot has a similar shaped from pre- to post-course with a definite rightward shift.



(b) Pre- and post-course FCI scores for non-traditional students. The post-course plot is a fairly flat pre-course distribution with a rightward shift in the post-course. The post-course scores are not normally distributed and contain a wide variety of scores.

Figure B.3: Pre- and post-course FCI scores for each status are displayed.

B.4.1 FCI Data

FCI means and standard error values are reported below for the Dataset D.

Table B.7: FCI Statistics for Dataset D

	n values			FCI Pre-Course		FCI Post-Course		FCI Gain	
Type	Pre-Course	Post-Course	Gain	Mean	Standard Error of Mean	Mean	Standard Error of Mean	Mean	Standard Error of Mean
All	95	69	57	11.89	0.58	16.90	0.75	4.93	.48
NT	19	16	11	14.2	1.1	17.6	1.6	5.9	1.0
Trad	76	53	47	11.33	0.65	16.70	0.86	4.72	.54

B.5 Dataset E

B.5.1 Network Data

Log Linear PageRank Plot

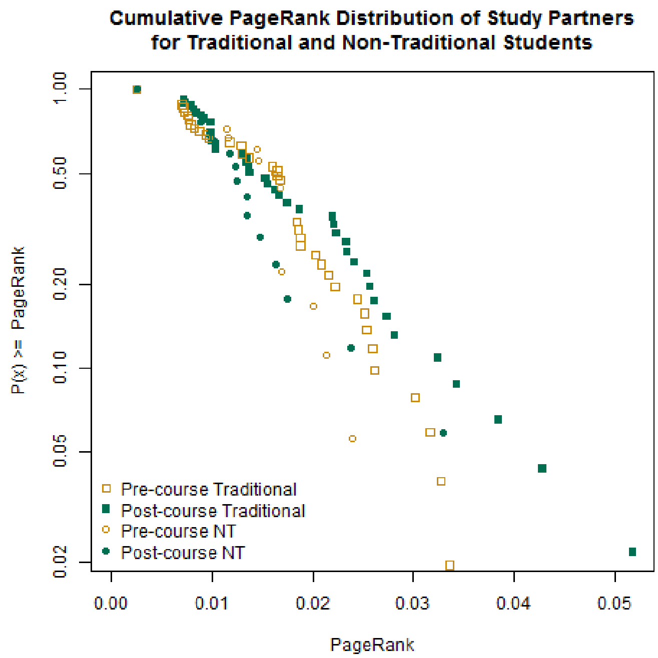


Figure B.4: The subsets of data are plotted together. It appears the non-traditional students tend to have a slightly lower pre-course PageRank. Throughout the course of the class, the difference between non-traditional students' PageRank and traditional students' PageRank is amplified slightly.

Network Statistics

Table B.8: SNA Statistics for Dataset E

(a) n values and Degree Statistics

	n values			Pre-Course Degree		Post-Course Degree		Degree Gain		Pre-Course Norm. Degree		Post-Course Norm. Degree	
Type	Pre-Course	Post-Course	Gain in Course	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	69	63	60	2.00	0.19	2.22	0.22	0.15	0.24	0.0294	0.0029	0.0358	0.0035
NT	41	30	27	1.51	0.30	1.76	0.33	0	0.45	0.0237	0.0045	0.0285	0.0053
Trad	161	144	134	2.14	0.24	2.40	0.27	0.20	0.29	0.0314	0.0035	0.00386	0.0043

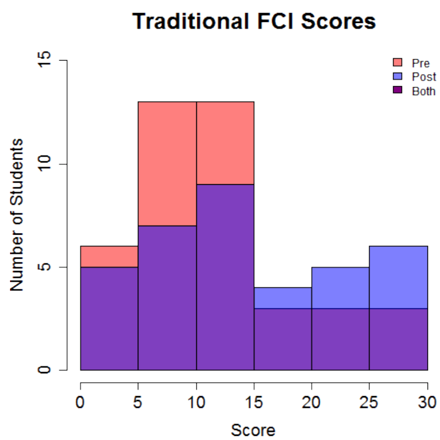
(b) (Normalized) Betweenness, Closeness, and PageRank Statistics

	Pre-Course Betweenness		Post-Course Betweenness		Pre-Course Closeness		Post-Course Closeness		Pre-Course PageRank		Post-Course PageRank	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	0.0273	0.0069	0.059	0.014	0.0274	0.0012	0.0759	0.0028	0.01449	0.00098	0.0159	0.0013
NT	0.0227	0.014	0.0574	0.0032	0.0245	0.0024	0.0728	0.0067	0.0128	0.0017	0.0126	0.0019
Trad	0.0289	0.0081	0.0598	0.0015	0.0284	0.00013	0.0771	0.0029	0.0151	0.0012	0.0171	0.0016

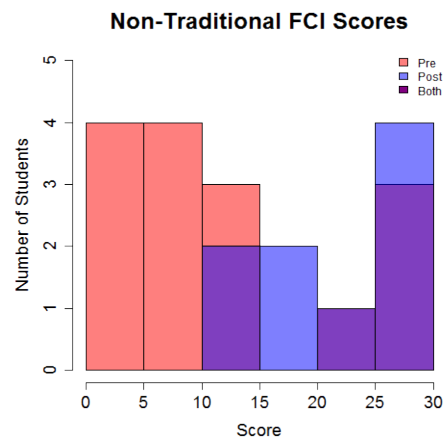
B.5.2 FCI Data

Histograms

Figure B.5 has both types of students showing a rightward shift. This is expected and positive, as it means that after instruction students answer questions about force concepts more accurately than without instruction. The non-traditional post-course results reveal a much more dramatic shift of learning.



(a) Pre- and post-course FCI scores for traditional students. Students seem to have gained, and the plot has a similar shaped from pre- to post-course with a dampened rightward shift. It does not appear traditional students were very dynamic in their gains.



(b) Pre- and post-course FCI scores for non-traditional students. The pre-course scores are not normally distributed and contain a wide variety of scores. Post-course shows a large rightward shift, symbolizing conceptual learning.

Figure B.5: Pre- and post-course FCI scores for each status are displayed.

This data set had FCI gain shapes similar to that of Dataset A.

FCI Statistics

FCI means and standard error values are reported below for Dataset E.

Table B.9: FCI Statistics for Dataset E

	n values			FCI Pre-Course		FCI Post-Course		FCI Gain	
Type	Pre-Course	Post-Course	Gain	Mean	Standard Error of Mean	Mean	Standard Error of Mean	Mean	Standard Error of Mean
All	56	45	35	12.3	1.0	16.7	1.3	4.20	0.82
NT	15	9	6	12.3	2.5	21.8	2.2	4.8	2.7
Trad	41	36	29	12.3	1.1	15.4	1.4	4.07	0.84

B.5.3 FCI and Network Data

Table B.10c provides mean and standard error values for FCI and network centralities.

Table B.10: FCI and SNA Statistics for Dataset E

(a) n values and FCI Statistics

	n values			FCI Pre-Course		FCI Post-Course		FCI Gain	
Type	Pre-Course	Post-Course	Gain	Mean	Standard Error of Mean	Mean	Standard Error of Mean	Mean	Standard Error of Mean
All	54	41	32	12.4	1.1	16.4	1.3	3.75	0.81
NT	14	9	6	12.4	2.6	21.8	2.2	4.8	2.7
Trad	40	32	26	12.4	1.1	14.9	1.5	3.50	0.80

(b) Degree Statistics

	Pre-Course Degree		Post-Course Degree		Degree Gain		Pre-Course Norm. Degree		Post-Course Norm. Degree	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	2.04	0.23	2.05	0.26	.06	0.31	0.0300	0.0034	.0330	0.0041
NT	1.57	0.39	1.33	0.33	0.50	0.50	0.0231	0.0057	.0215	0.0054
Trad	2.20	0.28	2.25	0.30	-0.04	0.37	0.0324	0.0042	.0363	0.0049

(c) (Normalized) Betweenness, Closeness, and PageRank Statistics

	Pre-Course Betweenness		Post-Course Betweenness		Pre-Course Closeness		Post-Course Closeness		Pre-Course PageRank		Post-Course PageRank	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	0.0258	0.0073	0.0508	0.016	0.0272	0.0013	0.0735	0.0039	0.0144	0.0012	0.0147	0.0015
NT	0.0253	0.018	0.0427	0.043	0.0231	0.0027	0.069	0.010	0.0124	0.0022	0.0099	0.0016
Trad	0.0259	0.0078	0.0531	0.0170	0.0286	0.0015	0.0747	0.0041	0.0151	0.0014	0.0160	0.0018

B.6 Dataset F Tables

B.6.1 Network Data

Network Statistics Tables

Table B.11: Number of nodes (n) and Degree Statistics for Dataset F

(a) n values and Degree Statistics

	n values			Pre-Course Degree		Post-Course Degree		Degree Gain		Pre-Course Norm. Degree		Post-Course Norm. Degree	
Type	Pre-Course	Post-Course	Gain	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	24	19	17	2.33	0.33	1.79	0.31	-0.82	0.31	0.104	0.014	0.099	0.017
NT	6	3	3	1.50	0.50	0.67	0.33	-0.7	1.2	0.065	0.022	0.037	0.019
Trad	18	16	14	2.61	0.38	2.00	0.34	-0.86	0.31	0.114	0.017	0.111	0.019

(b) (Normalized) Betweenness, Closeness, and PageRank Statistics

	Pre-Course Betweenness		Post-Course Betweenness		Pre-Course Closeness		Post-Course Closeness		Pre-Course PageRank		Post-Course PageRank	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	0.107	0.037	0.041	0.018	0.223	0.011	0.0895	0.0064	0.042	0.0046	0.0526	0.0060
NT	0	0	0	0	0.193	0.034	0.071	0.016	0.0274	0.0061	0.035	0.015
Trad	0.143	0.046	0.049	0.021	0.2327	0.0093	0.0931	0.0068	0.0464	0.0054	0.056	0.0065

B.6.2 FCI Data

Table B.12 gives mean and standard error values for the FCI pre- and post-course and gain scores of the whole class and each subset of students.

Table B.12: FCI Statistics for Dataset F. Not all students had demographic information to determine non-traditional status, so one data point is omitted from the status separated subsets.

	n values			FCI Pre-Course		FCI Post-Course		FCI Gain	
Type	Pre-Course	Post-Course	Gain	Mean	Standard Error of Mean	Mean	Standard Error of Mean	Mean	Standard Error of Mean
All	24	13	12	12.0	1.4	22.5	1.2	9.3	1.7
NT	8	2	2	10.1	1.6	25.0	1.0	10.0	3.0
Trad	15	10	9	12.2	1.9	21.5	1.4	9.6	2.2

B.6.3 FCI and Network Data

Table B.13 reports the results of Pearson correlations that were able to be performed. None were significant.

		All Data					
		FCI Pre-Course		FCI Post-Course		FCI Gain	
		r	p-value	*r*	p-value	*r*	p-value
All Data	Pre Degree	0.232	0.309	0.277	0.411	-0.0436	0.901
	Post Degree	0.121	0.671	0.0114	0.979	-0.0862	0.805
		Non-Traditional Data					
		FCI Pre-Course		FCI Post-Course		FCI Gain	
		r	p-value	*r*	p-value	*r*	p-value
Non-Traditional	Pre Degree	0.351	0.537	-	-	-	-
	Post Degree	-0.995	0.332	-	-	-	-
		Traditional Data					
		FCI Pre-Course		FCI Post-Course		FCI Gain	
		r	p-value	*r*	p-value	*r*	p-value
Traditional	Pre Degree	0.213	0.441	0.411	0.279	0.128	0.746
	Post Degree	0.242	0.441	0.282	.426	-0.139	0.731

Table B.13: Pearson Data Correlations For Degree and FCI values for full data and subsetted data. Non-traditional sample size is too small to provide correlation values. No p-values are below .05 so none of these correlations are significant.

n values and basic statistics for the dataset of students with FCI and network data are presented in Table B.14c.

Table B.14: FCI and Number of nodes (n) and Degree Statistics for Dataset F

(a) n values and FCI Statistics

	n values			FCI Pre-Course		FCI Post-Course		FCI Gain	
Type	Pre-Course	Post-Course	Gain	Mean	Standard Error of Mean	Mean	Standard Error of Mean	Mean	Standard Error of Mean
All	21	12	11	12.0	1.4	22.1	1.2	9.6	1.8
NT	6	2	2	11.5	1.8	25	1.0	10.0	3.0
Trad	15	10	9	12.2	1.9	21.5	1.4	9.6	2.2

(b) Degree Statistics

	Pre-Course Degree		Post-Course Degree		Degree Gain		Pre-Course Norm. Degree		Post-Course Norm. Degree	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	2.48	0.36	2.25	0.41	-0.73	0.38	0.108	0.015	0.125	0.022
NT	1.50	0.50	0.50	0.50	-1.5	1.0	0.065	0.022	0.02	0.028
Trad	2.87	0.42	2.60	0.40	-0.56	0.38	0.125	0.018	0.144	0.022

(c) (Normalized) Betweenness, Closeness, and PageRank Statistics

	Pre-Course Betweenness		Post-Course Betweenness		Pre-Course Closeness		Post-Course Closeness		Pre-Course PageRank		Post-Course PageRank	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	0.119	0.041	0.052	0.025	0.23	0.012	0.0964	0.0074	0.0435	0.051	0.0600	0.0076
NT	0	0	0	0	0.193	0.034	0.078	0.025	0.0274	0.0061	0.022	0.013
Trad	0.166	0.053	0.062	0.029	0.2387	0.0099	0.1000	0.0075	0.0499	0.0061	0.0675	0.0065

B.7 Dataset G Tables

B.7.1 Network Data

Table B.15: Number of nodes (n) and Degree Statistics for Dataset G

(a) n values and Degree Statistics

	n values			Pre-Course Degree		Post-Course Degree		Degree Gain		Pre-Course Norm. Degree		Post-Course Norm. Degree	
Type	Pre-Course	Post-Course	Gain	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	29	23	23	3.24	0.33	2.35	.26	-1.26	0.31	0.116	0.012	0.107	0.012
NT	6	2	2	2.33	0.71	2.5	1.5	-1.50	0.50	0.083	0.026	0.114	0.068
Trad	23	21	21	3.48	0.37	2.33	0.27	-1.24	0.34	0.124	0.013	0.106	0.012

(b) (Normalized) Betweenness, Closeness, and PageRank Statistics

	Pre-Course Betweenness		Post-Course Betweenness		Pre-Course Closeness		Post-Course Closeness		Pre-Course PageRank		Post-Course PageRank	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	0.067	0.016	0.055	0.016	0.2541	0.0097	0.1002	0.0064	0.0345	0.0031	0.0526	0.0060
NT	0.023	0.015	0.037	0.037	0.207	0.035	0.1165	0.0065	0.0264	0.0066	0.044	0.22
Trad	0.078	0.019	0.056	0.017	0.0266	0.0066	0.0986	0.0069	0.0366	0.0034	0.043	0.0042

No t-tests were completed as the non-traditional data set is too small to yield valid conclusions.

B.7.2 FCI Data

Table B.16 gives mean and standard error values for the FCI pre- and post-course and gain scores of the whole class and each subset of students. Table B.16 gives statistics on the FCI dataset. No t-tests were done due to the small sample size.

Table B.16: FCI Statistics for Dataset G

	n values			FCI Pre-Course		FCI Post-Course		FCI Gain	
Type	Pre-Course	Post-Course	Gain	Mean	Standard Error of Mean	Mean	Standard Error of Mean	Mean	Standard Error of Mean
All	30	21	21	10.47	0.82	18.9	1.3	8.10	0.86
NT	8	2	2	9.0	1.7	18.5	5.5	6.5	3.5
Trad	15	10	9	10.83	0.93	10.9	1.3	8.3	0.90

B.7.3 FCI and Network Data

Table B.17 contains the Pearson correlation tests for this dataset. No significant results were found.

		All Data					
		FCI Pre-Course		FCI Post-Course		FCI Gain	
		r	p-value	*r*	p-value	*r*	p-value
All Data	Pre Degree	0.124	0.524	0.107	0.634	0.759	0.743
	Post Degree	0.102	0.654	0.262	0.266	0.309	0.195
		Traditional Data					
		FCI Pre-Course		FCI Post-Course		FCI Gain	
		r	p-value	*r*	p-value	*r*	p-value
Traditional	Pre Degree	0.0976	0.667	0.279	0.242	0.205	0.396
	Post Degree	0.0798	0.74	0.358	.131	0.438	0.063

Table B.17: Pearson data correlations for degree and FCI values for full data and traditional data. Non-traditional sample size is too small to provide correlation values. No p-values are below .05 so none of these correlations are significant.

Table B.18 is a comprehensive table giving mean and standard error values for FCI and network centralities for the dataset.

The sample sizes and basic statistical values for the pre- and post-course datasets where network and FCI data was available are reported in Table B.16. Due to the small n values, no t-tests were performed. n values and basic statistics for the dataset of students with FCI and network data are presented in Table B.18.

Table B.18: FCI and Number of nodes (n) and Degree Statistics for Dataset G

(a) n values and FCI Statistics

	n values			FCI Pre-Course		FCI Post-Course		FCI Gain	
Type	Pre-Course	Post-Course	Gain	Mean	Standard Error of Mean	Mean	Standard Error of Mean	Mean	Standard Error of Mean
All	29	20	20	10.55	0.84	18.6	1.3	8.00	0.90
NT	6	1	1	9	-	13	-	3	-
Trad	23	19	19	10.96	0.97	18.9	1.3	8.26	0.90

(b) Degree Statistics

	Pre-Course Degree		Post-Course Degree		Degree Gain		Pre-Course Norm. Degree		Post-Course Norm. Degree	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	3.24	0.33	2.40	0.28	-1.30	0.35	0.116	0.012	0.109	0.013
NT	2.33	0.71	4	-	-1	-	0.083	0.026	0.18	-
Trad	3.48	0.37	2.32	0.28	-1.32	0.37	0.124	0.013	0.105	0.013

(c) (Normalized) Betweenness, Closeness, and PageRank Statistics

	Pre-Course Betweenness		Post-Course Betweenness		Pre-Course Closeness		Post-Course Closeness		Pre-Course PageRank		Post-Course PageRank	
Type	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean	Mean	Std. Error of Mean
All	0.067	0.016	0.057	0.018	0.2541	0.0097	0.0982	0.0072	0.034	0.034	0.0444	0.0043
NT	0.023	0.015	0.074	-	0.207	0.035	0.12	-	0.0066	0.0066	0.066	-
Trad	0.078	0.019	0.056	0.019	0.2664	0.0066	0.0969	0.0075	0.0366	0.0034	0.0432	0.0044

Appendix C

Survey Cover Sheet

Students will read this information before taking the surveys, and either agree or disagree to participate in place of a signed informed consent. If they do not agree, their results will not be saved or used for analysis, but they will still receive credit for participation.

Introductory physics courses include a variety of learning strategies in addition to lecture. The use of cooperative learning is designed to give you practice at working in groups, as professional scientists and engineers do, and to help your learning by collaborating on challenging problems. This semester, Dr. Adrienne Traxler will be evaluating this strategy in the course. The evaluation is important in determining how cooperative learning can best be used for this class, and how it can be improved. The evaluation data collected will not be a part of your grade for the course (there are no "right" or "wrong" answers on the surveys), but will be used for future planning.

If the evaluation of the learning strategies is useful, Dr. Traxler would like to share it with other educators and researchers to help them in teaching physics. Therefore, she is requesting permission to share the data you provide with other educators as part of a summary report and research work. These reports will be about results from the whole class, so you will not be identifiable as an individual. Your survey results will be kept only in password-protected electronic storage or locked physical storage, and only people who are part of the research project will have access. Survey responses will not be seen by your instructor during the semester, and so specific answers cannot influence your grade. All data will be treated confidentially, and if shared in the scientific literature, will not identify the particular class that provided the information.

This method of protecting your identity and the confidentiality of the data has been approved by the appropriate review board at Wright State University.

As part of taking PHY 2400, you are required to participate in all learning activities and to complete the pre-course, mid-semester, and post-course surveys. If you are unable to participate in the learning activities or surveys due to an excused absence, you will be given a written make-up assignment.

You do have an option to allow or not allow the information you provide as part of this evaluation of learning strategies to be shared with educators beyond this university. It is hoped that you will consent to including your data in the analysis, because there will be no way to identify you as an individual. After having any questions answered (email the instructor or Dr. Traxler, adrienne.traxler@wright.edu, with any questions), please indicate your willingness to have your data included as part of the summary report by checking the appropriate box below.

The consent question will be stored as part of the survey, and all will be kept on a password-protected website until the end of the semester. Dr. Traxler will not review which students have chosen to allow their data to be shared in a group summary until after the end of the semester and final grades have been posted.

- All my questions about the evaluation of the learning strategies and the confidentiality of any information I provide have been answered.
- I understand that all evaluation data I provide will be treated confidentially.
- I also understand that in the event a summary of the evaluation is shared with the wider educational community, no individuals providing data will be able to be identified.
- I further understand that if I have any additional questions about this evaluation or the procedure for maintaining the confidentiality of my data, I may call Dr. Traxler at 937-775-3139 or email her at adrienne.traxler@wright.edu.

I have read the cover letter and voluntarily: (check the appropriate response)

______ consent

______ do not consent

to allow my data to be included in a summary report shared with the wider education community.

Name: ______________________

UID: ______________________

Appendix D

Network Survey

This survey will be given at the beginning, midpoint, and end of the semester to collect information about learning community structures that form in the class.

The physics department is conducting several surveys to understand how to better accommodate learning in introductory physics courses. In this survey you will be asked to identify other students enrolled in this course that you have studied with or that you discuss physics concepts with. The responses will not be made public, and will not affect your grade.

1. What is your name?

2. What is your UID?

3. Who do you work with to learn physics? Please select as many students as you study with.

   [List of names from course roster]

Bibliography

[1] PageRank Centrality. `http://www.sci.unich.it/{~}francesc/teaching/network/pagerank`.

[2] *Student Fact Book, Fall 2015*. 39 edition, 2015.

[3] Jessie C Antonellis and Erik Brogt. Regulations and Ethical Considerations for Working with Human Participants in Physics and Astronomy Education Research. pages 1–18, 2012.

[4] Timothy Baldwin, Michael Bedell, and Jonathan Johnson. The Social Fabric of a Team-Based M.B.A. Program: Network Effects on Student Satisfaction and Performance. *Academy of Management*, 40(6):1369–1397, 1997.

[5] R J Beichner, J M Saul, D S Abbott, J J Morse, D Deardorff, R J Allain, S W Bonham, M Dancy, and J Risley. The Student-Centered Activities for Large Enrollment Undergraduate Programs (SCALE-UP) Project. *Physics*, 1(1):1–42, 2007.

[6] Robert Beichner. An Introduction to Physics Education.

[7] Phillip Bonacich. Power and Centrality: A Family of Measures. *American Journal of Sociology*, 92(5):1170–1182, 1987.

[8] Eric Brewe, Laird H. Kramer, and George E. O'Brien. Changing participation through formation of student learning communities. *AIP Conference Proceedings*, 1289:85–88, 2010.

[9] Jesper Bruun and Ian G. Bearden. Time development in the early history of social networks: Link stabilization, group dynamics, and segregation. *PLoS ONE*, 9(11), 2014.

[10] Jesper Bruun and Eric Brewe. Talking and learning physics: Predicting future grades from network measures and Force Concept Inventory pretest scores. *Physical Review Special Topics - Physics Education Research*, 9(2):1–13, 2013.

[11] Jacob Cohen. A power primer. *Psychological Bulletin*, 112(1):155–159, 1992.

[12] Karen S Cook, Richard M Emerson, Mary R Gillmore, and Toshio Yamagishi. The Distribution of Power in Exchange Networks : Theory and Experimental Results. *American Journal of Sociology*, 89(2):275–305, 1983.

[13] Ronald N Cortright, Heidi L Collins, and Stephen E DiCarlo. Peer instruction enhanced meaningful learning: ability to solve novel problems. *Advances in physiology education*, 29(2):107–111, 2005.

[14] Gabor Csardi and Tamas Nepusz. The igraph software package for complex network research. *InterJournal*, Complex Systems:1695, 2006.

[15] Shane Dawson. A study of the relationship between student social networks and sense of community. *Educational Technology & Society*, 11(3):224–238, 2008.

[16] L C Freeman. Centrality in Social Networks Conceptual Clarification. *Social Networks*, 1(3):215–239, 1979.

[17] Scott Freeman, Sarah L Eddy, Miles McDonough, Michelle K Smith, Nnadozie Okoroafor, Hannah Jordt, and Mary Pat Wenderoth. Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences of the United States of America*, 111(23):8410–5, 2014.

[18] Silvia Gilardi and Chiara Guglielmetti. University Life of Non-Traditional Students: Engagement Styles and Impact on Attrition. *The Journal of Higher Education*, 82(1):33–53, 2011.

[19] Renee Michelle Goertzen, Eric Brewe, and Laird Kramer. Expanded Markers of Success in Introductory University Physics. *International Journal of Science Education*, 35(2):262–288, 2013.

[20] Daniel Z Grunspan, Benjamin L Wiggins, and Steven M Goodreau. Understanding Classrooms through Social Network Analysis : A Primer for Social Network Analysis in Education Research. *CBE Life Sciences Education*, 13:167–178, 2014.

[21] Richard R Hake. Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses. *American Journal of Physics*, 66(1):64–74, 1998.

[22] Patricia Heller. Teaching problem solving through cooperative grouping. Part 2: Designing problems and structuring groups, 1992.

[23] Patricia Heller, Ronald Keith, and Anderson Scott. Teaching problem solving through cooperative grouping (Part 1): Groupe Versus Individuel Problem Solving., 1992.

[24] Charles Henderson. Common Concerns About the Force Concept Inventory. *The Physics Teacher*, 40(December):542–547, 2002.

[25] David Hestenes, Malcolm Wells, and Gregg Swackhamer. Force concept inventory. *The Physics Teacher*, 30(3):141, 1992.

[26] Douglas Huffman and Patricia Heller. What does the force concept inventory actually measure?, 1995.

[27] M. G. Kendall. Biometrika Trust. *Biometrika*, 38(1/2):11–25, 1951.

[28] Eric Kolaczyk and Gabor Csardi. *Statistical Analysis of Network Data with R*. Springer, New York, 2014.

[29] Peter V. Marsden. Survey Methods for Network Data. *The Sage Handbook of Social Network Analysis*, pages 370–388, 2011.

[30] Jeffrey D. Marx and Karen Cummings. Normalized change. *American Journal of Physics*, 75(2007):87, 2007.

[31] Eric Mazur. *Peer Instruction: A User's Manual*. Prentic Hall, 1997.

[32] Ian McCulloh, Helen Armstrong, and Anthony Johnson. *Social Network Analysis with Applications*. John Wiley & Sons, 2013.

[33] Erich Neuwirth. *RColorBrewer: ColorBrewer Palettes*, 2014. R package version 1.1-2.

[34] Lawrence Page, Sergey Brin, Rajeev Motwani, and Terry Winograd. The PageRank Citation Ranking: Bringing Order to the Web. *World Wide Web Internet And Web Information Systems*, 54(1999-66):1–17, 1998.

[35] S Provasnik and M Planty. Community Colleges: Special Supplement to the Condition of Education 2008. Technical Report I, Institute of Educational Statistics, U.S. Department of Education, Washington DC, 2008.

[36] R Development Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2008. ISBN 3-900051-07-0.

[37] Martin Rosvall and Carl T. Bergstrom. Mapping change in large networks. *PLoS ONE*, 5(1), 2010.

[38] RStudio Team. *RStudio: Integrated Development Environment for R*. RStudio, Inc., Boston, MA, 2012.

[39] V. Tinto. Classrooms as Communities. *The Journal of Higher Education*, 68(6):599–623, 1997.

[40] Transfer and Nontraditional Student Center. Nontraditional Students at Wright State, 2016.

[41] Wickham and Hadley. Reshaping data with the reshape package. *Journal of Statistical Software*, 21(12), 2007.

[42] Hadley Wickham. The split-apply-combine strategy for data analysis. *Journal of Statistical Software*, 40(1):1–29, 2011.

[43] Reza Zafarani, Mohammad Ali Abbasi, and Huan Liu. *Social Media Mining: An Introduction*. Cambridge University Press, 2014.