COLLABORATIVE LEARNING IN AN ASYNCHRONOUS ONLINE INTRODUCTORY STATISTICS COURSE

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Education at the University of Kentucky

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ABSTRACT OF DISSERTATION

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Collaborative learning has been shown to improve student learning and performance; however, the influence of collaboration has not yet been examined in the context of an online introductory statistics course. Often the influence of collaborative learning is measured using only one outcome variable, typically course achievement. This study will contribute a more thorough examination of the influence collaboration has on student learning by operationalizing the learning construct with the use of multiple measures: academic performance, perceived learning, and growth in statistical knowledge. In addition, this study will provide a model for incorporating collaborative learning in an asynchronous online course.

KEYWORDS: collaboration, online learning, introductory statistics

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CHAPTER 1. INTRODUCTION

1.1 Introduction

In 2004, McInnerney and Roberts wrote, “it is hoped that over the next few years, educators and academics working in higher education will be courageous enough to experiment more widely with …implementation of collaborative learning in an online environment” (p. 212). Now eighteen years later, collaboratively learning is still not a common occurrence in the online classroom. Collaborative learning has numerous benefits. It not only supports student learning in the classroom but trains students to work together for the communities they will become a part of after their formal educational training (Bruffee, 1999). Hiltz (1998), a pioneer in online education, defended collaborative learning was a necessity in fully online courses in order for them to be as successful as traditional face-to-race courses and stated, “colleges and universities ought to be concerned not with how fast they can ‘put their courses up on the Web,’ but with finding out how this technology can be used to build and sustain learning communities” (Hiltz, 1998, p. 7). However, in 2020, time was not a luxury that educators were given when adapting their courses to an online environment.

Collaborative learning has been shown to improve student learning and performance (Johnson & Johnson 2002a; Kurucay & Inan, 2017); however, the influence of collaboration on student learning has not yet been examined in the context of an online introductory statistics course. Many of the examples measuring the influence of collaborative learning in an online environment do so using only one outcome variable, often course achievement. This study will contribute a more thorough examination of the influence collaboration has on student learning by operationalizing the learning construct with the use of multiple measures.

The setting for this study was an asynchronous online introductory statistics course. There is little research detailing how collaborative activities occur within asynchronous courses (Oyarzun, Stefaniak, Bol, & Morrision, 2018). Many examples of asynchronous text-based discussion exist but these lack the face-to-face component, which Johnson and Johnson (2002b) defend, creates more effective collaboration. Hiltz (1998) claimed collaborative learning is only feasible with small classes; it will be argued that this is not the case. Collaborative learning in an asynchronous online statistics course is possible. This study provides a model that educators may use as a starting point for incorporating collaborative learning in this context.

The investigation was carried out among students enrolled in two online sections of introductory statistics at the researcher's higher education institution. Students in one section served as the control group. Students in the other section completed collaborative assignments and served as the treatment group. All other conditions of the two sections were the same. Student learning was measured using academic performance, perceived learning, and gains in statistical knowledge.

1.2 Statement of the Problem

Enrollment in online courses at higher education institutions continues to be on the rise even as overall enrollments are on the decline (Seaman, Allen, & Seaman, 2018). From 2012 to 2016, there was a 17.2% increase in the number of students taking at least one distance education course. However, attrition rates are estimated to be 10% to 20%

higher in online courses than in traditional face-to-face courses, and students report being more dissatisfied in online courses (Levy, 2007; Carr, 2000). Additionally, online courses often have fewer students that successfully complete the class than their face-to-face counterpart (Cavanaugh & Jacquemin, 2015; Callister & Love, 2016). This has been supported in online introductory statistics courses as well. Lu and Lemonde (2013) found that lower performing students in an online introductory statistics course had significantly lower test scores than compared to lower performing students in a face-to-face course; the scores on the final exam were 17 percentage points lower for the online students than the face-to-face students. Graduate students in a face-to-face introductory statistics course scored higher than 83.4% of graduate students that took the same course online (Christmann, 2017). Further, the number of students taking an introductory statistics course continues to increase; in 2010 there was a 34.7% increase from 2005 in the number of students taking an introductory statistics course (Blair, Kirkman, & Maxwell, 2010). Therefore, careful attention should be paid to improving online courses, specifically introductory statistics courses.

Many have associated high college dropout rates to student isolation and lack of engagement within their courses – both face-to-face and online (Tinto, 1993; Rovai, 2002). Several strategies have been identified for improving retention rates for students enrolled in online courses including, but not limited to, improving student engagement, learner centered approaches, and learning communities (Angelino, Williams, & Natvig, 2007). Active and cooperative learning are strong predictors of undergraduate students' educational and intellectual gains (Kuh, Pace, & Vesper, 1997). Johnson and Johnson (2002b) hypothesized that when students work together fewer will leave their university.

Collaborative assignments have been suggested to lessen students' feelings of isolation (Palloff & Pratt, 2001). In face-to-face courses, collaborative learning has been shown to enhance learning and improve student retention (Johnson & Johnson, 2002a). While it has been used in online courses, there has not been a consensus on whether collaboration improves student learning. For example, Alqurashi (2019) found learner-learner interactions in an online learning environment were not a significant predictor in perceived learning. However, others have observed that students in an online course performed significantly better in the course when working collaboratively than those that completed similar assignments individually (Kurucay & Inan, 2017). Further, the incorporation of collaborative learning tasks has not yet been shown to improve student learning in the specific context of an online introductory statistics courses.

1.3 Purpose and Significance of the Study

There have been some studies supporting that collaborative learning in online courses improves student achievement (Gunawardena, Linder-VanBerschot, Lapointe, & Rao, 2010; Kurucay & Inan, 2017). When students work collaboratively in asynchronous online courses their achievement is equal or better than that of traditional face-to-face courses that also include collaborative learning; however, when learners work individually in an asynchronous online environment their outcomes are worse than students working individually in face-to-face courses (Hitlz, Coppola, Rotter, Turoff, & Benbunan-Fich, 2019). Learners must justify their understanding of content to their peers when working collaboratively, which requires that students explain and organize their thoughts more deeply than if completing activities individually (Van Boxtel, Van der

Linden, & Kanselaar, 2000). Measuring knowledge growth is valuable for verifying the effectiveness of the collaborative strategy. However, few studies have investigated the influence of collaboration on student learning beyond academic achievement. Even fewer studies have shown how collaborative learning affects student learning in online courses within quantitative disciplines.

Many studies have examined how collaborative learning in online courses influence student satisfaction and engagement (Kuo, Walker, Schroder, & Belland, 2014; Thurmond et al., 2002; Cole, Lennon, & Weber, 2019; Stein, Wanstreet, Calvin, & Wheaton, 2005), though few have directly examined the influence on student learning. In Martin, Sun, and Westine's (2020) review of online teaching and learning from 2008 to 2017, only 5.17% of the studies researched learner outcomes. Even though the highest number of publications focused on learner engagement (28.92%), the sub-domain of collaboration only accounted for 2.75% of the total articles reviewed. The results of this study add to the limited body of work examining collaborative learning in online courses. This study quantifies the influence collaboration has on student learning in an asynchronous online introductory statistics course which has not yet been reported.

Additionally, lower performing students – as defined by having a GPA or course grade below the median – have been identified as having significantly lower grades in online courses than the same courses taught in a face-to-face format. This has been supported in a general setting that included over 5,000 courses taught by more than 100 faculty members (Cavanaugh & Jacquemin, 2015) and also in an undergraduate statistics course (Lu and Lemonde, 2013). Lower performing students benefit more from collaborative learning than higher performing students in face-to-face courses (Han, Capraro, & Capraro, 2015; Saner, McCaffrey, Stecher, Klein, & Bell, 1994). This finding has not been uncovered in online courses. The purpose of this study was to investigate how collaborative tasks influence student learning in an asynchronous online introductory statistics course. It was hypothesized that lower performing students who experienced collaborative learning in an online course would outperform lower performing students that worked individually in the same online course.

An additional goal was to provide a model for incorporating collaborative learning in online introductory statistics courses. There is little research detailing how collaborative activities occur in asynchronous courses in any discipline (Oyarzun, Stefaniak, Bol, & Morrision, 2018). The collaborative model applied in this study can be used as a guide for collaborative activities in any asynchronous online course, specifically those within quantitative disciplines. The structure of the collaborative meetings detailed here provides online educators a format for creating face-to-face interactions in an asynchronous course.

1.4 Research Questions

The main goal for this study was to explore collaborative learning in a specific setting. Therefore, the overarching research question for this study was: What influence does collaborative learning have on student learning in an asynchronous online introductory statistics course? In order to answer this overarching research question, the following ancillary questions were used for guiding this study:

1. To what degree does student learning differ among students that work collaboratively in an asynchronous online introductory statistics course compared with students that work individually in the same setting?
2. To what degree does student learning differ among lower performing students that work collaboratively in an asynchronous online introductory statistics course compared with lower performing students that work individually in the same setting?
3. To what degree does collaborative learning contribute to student learning in an asynchronous online introductory statistics course?

1.5 Organization of the Dissertation

This dissertation is organized into five chapters. Chapter 1 was an introduction which included the purpose and significance of the study as well as the research questions. Chapter 2 is a review of the relevant literature of collaborative learning in higher education, online courses, and introductory statistics. Chapter 3 describes the methodology implemented for this research study. Chapter 4 includes the data analysis and resulting outcomes. Chapter 5 discusses the results and implications for online educators and future research.

CHAPTER 2. LITERATURE REVIEW

Lack of student engagement is a far-reaching problem within higher education. Higher education administrators and faculty members are continually seeking ways to get students involved on their campuses and in their classrooms for ultimately improving student success at their universities and colleges. Collaborative learning is one method for creating an active online learning environment and improving student learning.

This review begins by defining collaborative learning. Then the historical progression of collaborative learning is outlined. This study took place where higher education, online learning, and statistics education overlap. Therefore, this review was conducted by examining collaborative learning in all three of those contexts, starting more broadly and then narrowing the focus to collaboratively learning in online statistics courses. Lastly, how researchers have measured learning in these contexts is reviewed. When searching for this review keys words such as collaborative learning, learner-learner interactions, student engagement, computer-supported collaborative learning, online learning, and asynchronous courses were used.

2.1 What is Collaborative Learning?

In a traditional learning environment, the instructor is often the center of the classroom and delivers information via lectures and printed and/or electronic materials. Learning takes place without collaboration and students function individually (McInnerney & Roberts, 2004). Traditional classrooms support an individualistic learning environment, where students learn by working by themselves (Johnson, Johnson, & Smith, 2014). In contrast, a collaborative learning environment improves learning through student interactions (McInnerney & Roberts, 2004). Collaborative learning environments aim for students to have shared responsibility while being socially and intellectually engaged (Smith & MacGregor, 1992). Students may need to justify their thinking in a collaborative group which leads to a deeper understanding (Dillenbourg and Schneider, 1995). Collaboration does not alter what students are learning in traditional classrooms; instead, it shifts how they are learning into a social context (Bruffee, 1992). There is a shift from “independence to interdependence and from a subjective to an intersubjective sense of identity” (Dirkx and Smith, p. 151, 2004).

2.1.1 Collaborative Versus Cooperation

Often the terms collaboration and cooperation have been used interchangeably. However, while similar, each approach to learning is unique, and it is important to note their distinctions. Students work together on a common objective when learning both collaboratively and cooperatively. What distinguishes collaboration from cooperation is the level of interdependence. Graham and Misanchuk (2004) define collaborative groups as having the highest level of interdependence, while cooperative groups have a lower level of interdependence (Figure 2.1)

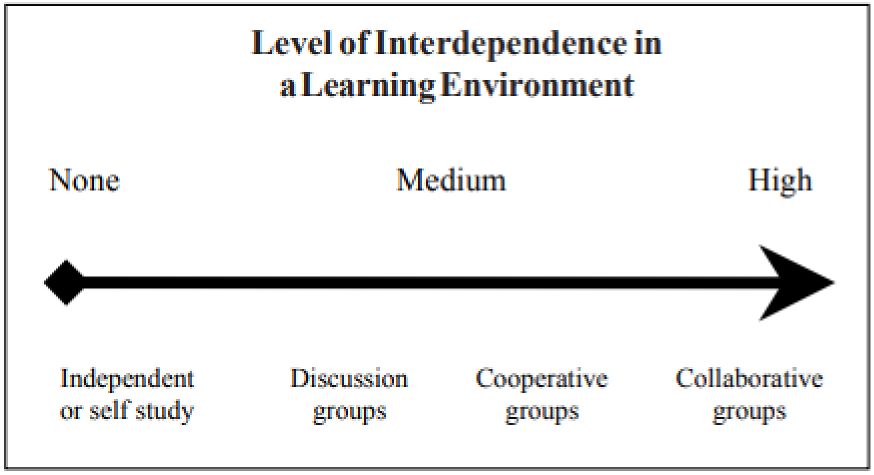


Figure 2.1 Levels of Interdependence in a Learning Environment (Graham & Misanchuk, 2004)

Interdependence is a necessity for all collaborative activities, resulting from all students contributing and feeling responsible for the end product (MacGregor, 1992). When students participate in collaborative learning each learner's input is valued; whereas, there is less emphasis on individual efforts in cooperative learning (McInnerney & Roberts, 2004). Others have stated that during collaborative learning, teams work together when finding solutions or interpretations (Smith & MacGregor, 1992), but cooperation can sometimes resemble a divide and conquer approach to completing a task (Dillenbourg, 1999).

Cooperation has been identified as a type of collaboration (Reychav & Wu, 2015) and is often embedded within collaborative learning. Alavi (1994) identified cooperation as a basic principle required for effective collaborative learning. Pantiz (1999) argued that students must cooperate within groups for establishing a consensus when learning collaboratively. Cooperative learning is often a structured approach within collaborative learning where tasks are specifically defined (Pantiz, 1999; Smith & MacGregor, 1992).

Therefore, groups may have less autonomy when operating cooperatively rather than collaboratively.

2.2 Historical Progression of Collaborative Learning

Collaborative learning is rooted in constructivist and social learning theories. The first collaborative learning principle Alavi (1994) listed for learning to be effective was "active learning and construction of knowledge." Collaboration by definition involves working with others and therefore is a social process. When examining how collaborative learning has progressed through time, one must begin by first considering constructivist and social learning theories.

2.2.1 Learning as a Social and Constructive Process

Learning often occurs through a social process of active knowledge construction. Piaget said active construction occurs through individual activities. Wadsworth (1971) summarized Piaget's views of learning as organizing and adapting an individual's environment. Learners assimilate – classify new stimuli into existing cognitive structures – or accommodate – create or modify cognitive structures to fit new stimuli – as part of the learning process. Assimilation and accommodation both require making connections to previously learned information. This may take place in social settings. However, Piaget's theory does not place enough emphasis on the role of the social environments in which the assimilation and accommodation occurs (Littleton & Häkkinen, 1999).

Learning develops as individuals take part in social interactions. Vygotsky held the view that the knowledge construction process occurs socially. He originated the "zone of proximal development." The zone of proximal development (ZPD) is the space between what learners actually know and what they have the potential for knowing. Potential knowledge can be gained through support from teachers and/or peers. Like Piaget, Vygotsky advocated learning expands through interaction with one's environment, but Vygotsky asserted learning also occurs in collaboration with others (Vygotsky, 1935/1978). James thought educators should examine what learners can do with assistance rather than relying on their own skills. "We are all too apt to measure the gains of our pupils by their proficiency in directly reproducing in a recitation or an examination . . . and inarticulate power in them is something of which we always underestimate the value" (James, 1899/2001, p. 69). Lave and Wenger (1991) described situated learning as knowledge gained naturally within activities. Learners become members of a "community of practice" sharing common beliefs and actions. Brown, Collins, and Duguid (1989) claimed collaborating and constructing knowledge in social atmospheres encourages learning. Authentic experiences are typical behaviors of everyday culture. These ideas form a foundation upon which collaborative learning is built.

2.2.2 Beginnings of Collaborative Learning

It is difficult to pinpoint exactly when collaborative learning first made its appearance in education; there have long been forms of collaborative learning but may not have been named as such. For example, in the late 1770's a professor at the University of Glasgow designed a peer review method (Gaillet, 1994). More recently, in the late 1960's the Guided Design approach was developed at West Virginia University's engineering program (Smith & MacGregor, 1994). This approach has been described as a method of teaching in which students learn by developing solutions to open-ended problems in small groups with teacher guidance (Lawrence, 2014). The term collaborative learning was officially given its name in the 1960's by a group of British educators. The first supporters of collaborative learning were committed "to democratizing education and to eliminating from education what were perceived as socially destructive authoritarian social forms" (Bruffee, 1992. p. 30) in response to the political environment during the time of the Vietnam War. During the 1960's in the US, new educational developments began to resemble collaborative learning. Group work began in elementary and secondary education and then slowly made its way into higher education (Gamson, 1994). A book titled *Collaborative learning* was published in 1970 (Mason). Then in 1975, Johnson and Johnson released *Joining together: Group theory and group skills*, a seminal book in the fields of cooperative and collaborative learning. Collaborative learning became a "catch phrase" in education in the 1980's and 1990's (Smith & MacGregor, 1994).

There were several forms of collaborative learning in its early years. This included various types of problem centered instruction including guided design, case studies in which students work in small groups to discuss problems, and simulations where students play the roles of opposing views. Other examples of collaborative learning are writing groups, discussion groups, learning communities, and peer teaching such as supplemental instruction and math workshops (Smith & MacGregor, 1992).

The benefits of collaboration in educational settings are plentiful. Collaborative learning creates "a community of learners in which everyone is welcome to join, participate, and grow" (Smith & MacGregor, p. 22, 1994). Learners gain interpersonal, intercultural, and higher-level thinking skills through collaboration that will be valuable outside of the classroom (Johnson & Johnson, 1991). Some students yearn to interact with their peers and value the different views they encounter in small groups (Dirkx & Smith, 2004). Other benefits that students have reported are improved listening skills, higher confidence, seeing how class topics can be applied, and learning how to respectfully disagree with others. From the faculty viewpoint, collaborative learning is thought to enhance assessments, allows for deeper understanding of both their students and subject matter, and invigorates their teaching experience (Smith & MacGregor, 1994).

There continues to be hesitancy for educators to incorporate collaborative learning in to their courses due to the number of challenges they may face. Students may oppose collaborative tasks when they view themselves as having a passive role in the learning process. When collaborative tasks are not designed appropriately students may become dissatisfied and view it as another thing to check off the to-do list (Dirkx & Smith, 2004). Students may discover ways to change collaborative assignment into smaller components to be completed individually (Kitchen & McDougall, 1999). Dillenbourg (1999) described this divide and conquer method as cooperation rather than collaboration. If students work individually, then elements of the collaboration may be removed along with the "energy and enthusiasm associated with the work" (Dirkx & Smith, 2004). When this occurs, learning is not as strong as if the task were completely collaboratively as intended. Much is expected of the students when learning collaboratively. It "demands responsibility, persistence, and sensitivity" (Smith & MacGregor, 1994, p. 22). Faculty may be incentivized against using collaborative learning. It requires more time and the instructor-centered, lecture model is prominent in higher education (Smith & MacGregor, 1992).

2.2.3 Collaborative Learning in Higher Education

Collaborative learning started to grab the attention of educators at post-secondary institutions in the US in the 1980's (Bruffee, 1992). During this time the American Association for Higher Education (AAHE) formed the Collaboration in Undergraduate Education action community (Gamson, 1994). Collaborative learning began an experimental solution to a problem in higher education; many students struggled in traditional courses. Colleges and universities were providing tools and help options outside of the classroom that were not getting used. To address this, strategies like peer tutoring followed by small group work were brought into the classroom (Bruffee, 1992).

The Association of American Colleges and Universities classify collaborative assignments and projects as a high-impact educational practice. The high-impact practices are teaching and learning practices that have been shown to increase student retention and engagement. There are two main goals for collaborative learning in higher education: working together to solve problems and strengthening individual understanding by gaining perspective from a diverse set of learners (AAC&U, 2008).

Collaborative learning has been incorporated within a variety of higher education contexts. Researchers have investigated a variety of collaborative learning approaches and designs in face-to-face courses; a few will be highlighted here. Cox (2015) examined the influence of individual pre-work before a general chemistry recitation. This assignment was then built upon in small groups and students then worked new problems together. Students using this model scored significantly higher on exams than those that had a traditional recitation; in the sample used the mean final exam score was 17 percentage points higher for the students that completed pre-work. Loes, An, Saichaie, and Pascarella (2017) uncovered collaborative learning produced more positive peer interactions and that is correlated with an increased likelihood of continuing on to the next college year. Al Mulhim and Eldokhny (2020) compared the influence of group size in collaborative projects and discovered groups of 7 or 8 students outperformed groups of 3 or 4 students.

The focus of this review of collaborative learning is primarily within online environments. Therefore, further investigation of the influence of collaborative learning in higher education will be described within the setting of online courses.

2.2.4 Online Collaborative Learning

The first forms of distance education came about based on the technology that was available at that time. In the 1950s, for example, television stations joined forces with universities to offer college courses. Following the invention of the World Wide Web, online courses and programs became more readily available. In 1998, the US began to see a rise in online education when New York University launched NYU Online. Many programs soon followed, though many were not long-lived (Palvia et al., 2018). Many higher education institutions began experimenting with hybrid programs in the early 2000s due to the early failure of many fully online programs. This is also when online courses started to more widely utilize tool such as discussion boards, chat rooms, and video conferencing (Palvia et al., 2018), all of which provided virtual spaces for collaborative learning.

2.2.4.1 Computer-Supported Collaborative Learning

Computer-supported collaborative learning (CSCL) began to makes an appearance in the 1990s as a response to the computer programs available at the time that constrained students to individual learning. CSCL drives the creation of new electronic tools that enable learners to come together for learning exploration and social interaction (Stahl et al. 2006). At its core, CSCL is learning together with the use of computers.

The authors of a 2009 review of computer-supported collaborative learning identified three stages within CSCL research (Dillenbourg, Järvelä, & Fischer). The first stage of CSCL began in 1990 after an absence of collaborative learning in educational technology. During this stage, knowledge was gained about the learning and social interactions that take place from the use of CSCL. From 1995 to 2005, CSCL gained attention in the scientific community and researchers examined all aspects of CSCL from the design to the analysis. After 2005, computer-supported collaborative learning became "integrated within comprehensive environments that include non-collaborative activities stretching over the digital and physical spaces and in which the teacher orchestrates multiple activities with multiple tools" (Dillenbourg, Järvelä, & Fischer, 2009, p. 4)

More recently, researchers have focused on a wide range of topics within computer-supported collaborative learning. Various approaches to CSCL continue to be compared by analyzing student learning and satisfaction (Mittelmeier, Rienties, Tempelaar, Hillaire, & Whitelock, 2018). Others have investigated how student learning is affected by teacher-student and student-student interactions, group support, and online collaborative tools (Hernández-Sellésa, Muñoz-Carrilb, & González-Sanmamed, 2019). Computer-supported collaborative learning gives a glimpse in to online collaborative learning. In CSCL, learners may share and construct knowledge synchronously or asynchronously online or in a physical classroom using computers (Stahl et al. 2006). CSCL it is not restricted to fully online courses and may be utilized in face-to-face courses. There may be additional barriers to consider – as well as advantages – when implementing collaborative learning in fully online courses.

2.2.4.2 Collaborative Learning in Online Courses

While computer-supported collaborative learning often spotlights the software that makes the collaboration possible, collaborative learning in online courses may not need any specific tools other than a virtual meeting space for discussions. These discussions may happen via text, voice, video, or any combination of these and may take place either synchronously or asynchronously. Collaborative learning in online courses has transformed with technology. Rovai (2002) urged online educators to build community in virtual environments especially in asynchronous courses. During that time in online education student interactions were only text-based; they did not see or hear one another and were not online at the same time. Discussion boards have been widely used as a way of implementing collaborative learning into online courses (e.g. Eastman & Swift, 2002; Cox & Cox, 2008; Xie, Chien, & Bradshaw, 2014). Aloni and Harrington (2018) identified one of the biggest challenges in using online discussion boards is students often have little to no participation. New forms of collaborative learning started to emerge as new technology was available. VoiceThread, for example, provides students more understanding and meanings in their peers' posts than text-based discussion boards, though participation may still be at the minimum amount required (Ching & Hsu, 2013). Both of these tools lack the face-to-face component which makes collaborative learning in online courses more difficult. Learners have reported being dissatisfied with collaborative tasks that have no face-to-face contact with group members (Thurmond et al., 2002).

Many students struggle to learn in online environments. Online courses often have higher dropout rates and students do not perform as well as in face-to face courses (Carr, 2000; Levy, 2007; Callister & Love, 2016). Some have found that higher performing students do even better or the about the same in online courses than in face-to-face courses; whereas, lower performing students have significantly lower grades in online courses (Lu & Lemonde, 2013; Cavanaugh & Jacquemin, 2015). In these studies, lower performing students were identified by either their cumulative GPA or by being below the median grade in the course. Therefore, online instructors should design courses aimed at improving course achievement in lower performing students. One method that enhances success for struggling students is collaborative assignments. Particularly, group work and project-based learning in face-to-face courses has resulted in significant improvements in learning for lower performing students (Saner et al. 1994; Webb, Nemer, Chizhik, & Sugrue, 1997; Hooper & Hannafin, 1998; Han, Capraro, & Capraro, 2015). Collaborative learning has not yet been shown to improve learning for lower performing students in online courses. Thus, the influence collaborative assignments have on learning for lower performing students ought to be examined in online environments.

Online educators must carefully design student interactions; just being together does not improve learning. There is no promise that learners will work together on collaborative assignments even when the expectation is that they do so (Dillenbourg, 1999). Interactions designed with high levels of intended collaboration positively affect learner performance (Oyarzun et al., 2018). Group work within collaborative learning environments is better managed when there are students that have previously taken at least one online course and/or the group contains adults over 30 years old. (Xu, Jianxia, & Fan, 2015). Pre-work tasks may provide richer text-based posts in asynchronous online discussion and deeper learning of course content (Koszalka, Pavlov, & Wu, 2021). Collaborative assignments in online courses should be designed so that students are pushed to work together to accomplish a common objective (Nooijer, Schneider, & Verstegen, 2020)

2.2.5 Collaborative Learning in Statistics

Numerous statistical organizations defend collaborative learning as a necessity in statistics classrooms. Leaders of five professional mathematical and statistical associations – AMATYC, AMS, ASA, MAA, and SIAM – examined seven curricular guides and identified communication as one of the common themes that would lead to improvement in mathematical sciences education (Saxe & Braddy, 2015). The document states, “Students must learn to communicate complex ideas in ways that are understandable to collaborators, clients, employers and other audiences” (p. 17). One of the recommendations in the 2016 Guidelines for Assessment and Instruction in Statistics Education (GAISE) College Report is to “foster active learning.” The GAISE College Report also suggests that instructors make use of small group work for encouraging students to learn from one another. The American Statistical Association (2014) suggests that statistics majors develop statistical practice by learning how to effectively communicate statistical ideas and listen to the needs of a client. Communication skills should be taught by requiring students to write, present, and visualize their ideas while collaborating with a team. The AP Statistics curriculum also places importance on communication by requiring students to write explanations and organize their work in free-response questions (College Board, 2010). The National Council of Teachers of Mathematics encourages social interaction in mathematics through the Communication Process Standard (NCTM, 2000). One component within this standard requires students to share mathematical ideas using clarity with their peers and teachers. Communication is key in all above mentioned documents. Collaborative learning allows students to experience the type of discourse described above.

The field of statistics has become more prominent with the surge in the amount and accessibility of data. The study of statistics is vital in the current information age (Wild & Pfannkuck, 1999). Collaboration in statistics courses is crucial for developing students into informed citizens. Students must recognize when statistics are misused. The general public may latch on to inaccurately manipulated data for supporting issues they wish to promote if they are statistically uneducated.

> In a variety of situations, statistical descriptions don't simply or neutrally record what's out there. There are political struggles/choices involved in: which data are collected, which numbers represent the most accurate data, which definitions should guide how the data are counted, which methods should guide how the data are collected, which ways the data should be disaggregated, and which are the most truthful ways to describe the data to the public. (Frankenstein, 2013, p. 37)

Introductory statistics courses must provide opportunities for students to communicate their statistical reasoning. All people encounter data in their daily lives and should "be more than just data crunchers. They should be data problem solvers … understanding that the *art of communication with data is essential* [emphasis added]" (Bargagliotti et al., 2020, p. 8). Therefore, it is clear collaboration should be implemented into statistics courses. The influence collaborative learning has on student learning within statistics course will be examined.

2.2.5.1 Relationship Between Statistics and Mathematics

Much of what has been researched about collaborative learning in statistics has been built upon work in the mathematics classroom. Therefore, a brief moment to discuss the relationship between mathematics and statistics is needed. Mathematics and statistics are extremely connected; however, there are distinctions between the two disciplines. Some have described the relationship between statistics and mathematics as a “marriage” (Scheaffer, 2006). Other have described the relationship between the two as having more tension. Those on the side of unity between mathematics and statistics urged that the teaching of statistics should not be the same as mathematics but that the two should strengthen each other (Scheaffer, 2006). Some mathematical organizations and standards include statistics at part of the curriculum. The NCTM includes “Data Analysis and Probability” as one of the five content standards (NCTM, 2000). The Common Core State Standard for Mathematics includes a probability and statistic domain. Further, the Mathematical Association of American Curriculum Guide recommends that every undergraduate mathematics major take an introductory applied statistics course (Cleary, Gabrosek, Lock, Parker, & Rossman, 2015). Rossman, Chance, and Median (2006) described statistics as a scientific field that makes use of mathematics; it is a separate field and not just a branch of mathematics. Moore and Cobb (2000) would agree with Rossman et al. and defended that statistics is much more than a sub-field of mathematics.

Regardless on one’s view about the relationship between mathematics and statistics, educators can learn from collaborations taking place in mathematics courses.

2.2.5.2 Collaborative Learning in Mathematics Courses

Various forms of collaborative learning have been incorporated into math courses and have been shown to be advantageous to students. Group work improves student achievement in mathematics (Sofroniou & Poutos, 2016) and active learning has been shown to improve student learning in mathematics and other STEM disciplines (Freeman et al., 2014). Collaborative learning has been found to be more effective than individual learning when tasked with solving new problems in mathematics (Retnowati, Ayres, & Sweller, 2017).

There is an abundant of examples stating the benefits of collaborative learning when compared to individual learning. However, many of those examples do not compare the effectiveness of the diverse forms of collaborative learning. Maharani, Marsigit, and Wijaya (2020) found the Three Steps Interview (TSI) collaborative learning model to be more effective on student achievement than Think Pair Share. Using TSI model, students discuss problems by asking and answering questions about what they are learning. Based on the definitions given previously, the TSI model is a collaborative form of learning, whereas Think Pair Share is a cooperative form. Hence, this study suggests that collaborative learning is more beneficial for students than cooperative learning.

Challenges of collaboration have been discussed, but there are some hurdles that are unique to utilizing collaborative learning in online mathematics courses. Nason and Woodruff (2004) identified two reasons why it is often difficult to support collaborative learning in mathematics in online environments. First, many textbook-type questions do not encourage discourse during or after the problem has been solved. Also, many online environments are limited in their use of mathematical representations and their ability to foster discourse. Thus, mathematical collaboration must include real-world problems that get students participating in the development of models that can then be evaluated and modified as necessary by students. There must also be tools available to allow for this type of collaboration. Similar challenges may exist in statistics.

2.2.5.3 Collaborative Learning in Introductory Statistics

The push for collaborative learning in introductory statistics began in the early 1990s in the form of cooperative learning. Cobb (1992) recommended statistics instruction include "group problem solving and discussion" as a way of encouraging active learning. An article in the first publication of the *Journal of Statistics Education* advocated for the use of cooperative group work for improving student learning (Garfield, 1993). Around the same time cooperative learning was also the focus of an article published in *Teaching Statistics* (Keeler & Steinhorst, 1994). Statistic educators have been advocating that teachers make use of collaboration in statistics courses for some time (Roseth, Garfield, & Ben-Zvi, 2008). Many of the early attempts using collaborative learning have lacked interdependence and, therefore, resembled cooperative learning instead. Hulsizer and Woolf (2008) included cooperative learning as an instructional technique for best teaching of statistics. Collaborative learning – or cooperative learning – has been used in introductory statistics course, but students have reported being dissatisfied with the experience. In a questionnaire completed by upper-level students enrolled in communication and business courses, not one student listed a mathematics or statistics course as the course in which they had the most positive group experience (Fiechtner & Davis, 1994).

There are few studies reporting the efficacy of learning statistics within small groups at the post-secondary level within the realm of statistics education; however, those that exist demonstrate that collaborative learning positively impacts student performance in introductory statistic courses (Kalaian & Kasim, 2014). Much of the research of collaborative learning in introductory statistics has been completed with psychology majors as the main audience. Typically, students majoring in psychology have to complete at least one course in statistics. Several researchers have observed collaborative learning improves learning for these students in introductory statistics courses. When team-based learning was a part of students' introductory statistics course, students earned slightly higher grades in the course and entered a follow-up research methods course more prepared than students that did not have team-based learning in their introductory statistics course (Campbell & Taylor, 2019). An escape room type of collaborative activity was another strategy used for getting psychology majors engaged in an introductory statistics course (McIntyre, 2020). Students that participated in the collaborative activities had a significant increase in their content knowledge. Collaborative testing is one more form of collaborative learning that has been implemented in introductory statistics courses having primarily psychology students (Eastridge & Benson, 2020). Some students took an individual test followed by a group test, others completed a group test first followed by an individual test, and final group of students did not have any group tests. The students that took the group test first had significantly higher individual test grades and final grades than the other two groups of students. This suggests it is more beneficial for students to participate in collaboration prior to individual assessment.

There is a need for examining the influence of collaborative learning on student learning in introductory statistics courses with a more diverse group of students. Once such study with a general audience used collaborative testing (Kapitanoff & Pandey, 2018). Students completed tests in pairs or individually. Not surprising was that scores on the collaborative tests were significantly better than individual test. However, there were no significant differences in the individual cumulative final exam scores for the two group of students. This implies that this type of collaboration has little influence on student learning.

2.2.6 Collaborative Learning in Online Introductory Statistics Courses

The context of the proposed study is at the intersection of higher education, online education, and introductory statistics. Collaborative learning, or some form of it, has been shown to support student learning in all three environments. Further, organizations from all three have identified collaborative learning as a method for effective teaching. Therefore, there is no question as to whether or not collaborative learning should be a part of online asynchronous introductory statistics courses. However, there is little empirical evidence claiming collaborative learning improves student learning in online introductory statistics courses.

Researchers have compared student learning in online introductory statistics courses with that of students in face-to-face courses (Summers, Waigandt, & Whittaker, 2005; Lu & Lemonde, 2013), assessed student satisfaction with an online statistics course or specific elements of the course (Tudor, 2006; Al-Asfour, 2012), and examined online students' attitudes towards statistics (Suanpang, Petocz, & Kalceff, 2004). Few, though, have examined distinct characteristics that may lead to improve outcomes for statistics students within online environments. Specifically, there have been few empirical studies examining teaching and student learning in online statistics courses (Mills & Raju, 2011). There have been some efforts describing how one might implement collaborative learning into online statistics courses; however, those endeavors lack empirical data (Sloboda, 2005; Everson, & Garfield, 2008). In Mills and Raju's 2011 review of teaching statistics online there were zero empirical studies examining the influence collaboration has on student learning.

After an extensive search for studies examining the influence of collaborative learning within the context of online introductory statistics courses, only one was observed. Bjornsdottir, Garfield and Everson (2015) utilized two models of collaborative test – consensus and non-concensus – in an online introductory statistics course. The researchers found no significant differences in students' performance among the two collaborative test models, though both groups improved in their attitudes toward statistic. Clearly, there is a vast hole in the collaborative learning literature in the setting of online introductory statistics. Hence, measuring how it influences student learning in this context is critical.

2.3 Measuring Student Learning

Researchers have used a variety of methods for measuring student learning in online settings. The one most dominant in research is course achievement and academic performance. Others have relied on student-reported learning. Researchers have utilized a variety of instruments when specifically inspecting students' knowledge of statistics.

2.3.1 Academic Performance and Course Achievement

The most prominent method for measuring student learning outcomes is by using course achievement and/or academic performance (Hiltz & Wellman, 1997). Online educators have investigated performance on individual assignments, exams, and final exams. Several researchers have used academic performance and course achievement to compare student learning in online courses to that of face-to-face and/or hybrid courses in a variety of disciplines (Cavanaugh & Jacquemin, 2015; Callister & Love, 2017; Yen, Lo, Lee, & Enriquez, 2018) and in statistics courses (Summers et al., 2005; Lu & Lemonde, 2013).

In the collaborative learning literature there are examples of measuring student learning based on their performance on collaborative tasks. Kurucay and Inan (2017) used scores on goal-based scenario assignments for comparing student learning outcomes in students that completed the assignments in groups with that of students that completed the tasks individually. However, this may be a more appropriate strategy when comparing similar collaborative learning experiences among different groups of students or when comparing different collaboration methods. On such example compared group achievement of Chinese and Flemish students that completed online group assignments (Zhu, 2012). Rovai, Wighting, Backer and Grooms (2009) argued that grades may not be the best way of measuring student learning since students may have knowledge of the content prior to taking a course or grade calculations may include non-learning factors such as participation, submitting assignments on time, and class attendance. Another concern with using academic achievement to measure student learning is that these instruments often have not been assessed for reliability or validity. Course achievement and academic performance are likely useful methods for comparing student learning in many settings, although it would be beneficial to extend the measurement of student learning to include instruments that have been found to have acceptable reliability and validity.

2.3.2 Perceived Learning

Perceived learning, or self-reporting learning, has been shown to have a strong positive relationship with academic achievement and to be a valid measure of student learning (Pike, 1995; Chesebro & McCroskey, 2000; Holden & Rada, 2011). Conversely, it has been stated that learner-learner interactions in an online environment are not a significant predictor of perceived learning (Alqurashi, 2019). However, in that study perceived learning was measured by students' response to one item. Therefore, further examination is need for understanding how learner-learner interactions may support learning. Self-reported learning was first used to measure student learning by Richmond, Gorham, and McCroskey in 1987. Perceived learning was first measured in a distance education course in the early 1990s among adult learners in televised courses (Walker & Hackman, 1992). Researchers continue to use self-reported learning for operationalizing learning.

Alavi (1994) developed a perceived learning scale adapted from a questionnaire created by Hiltz (1988) that evaluated the effectives of an online course. Alavi's perceived learning scale has been used for measuring student learning outcomes by a variety of researchers (Chen & Jang, 2010; Chen, Jones, & Xu, 2018). This scale has also been used to assess the effectiveness of collaborative learning. Bravo, Catalán, and Pina (2019) used an adapted version of Alavi's perceived learning scale as a way of measuring team effectiveness. Kurucay and Inan (2017) implemented portions of Alavi's scale to compare learning in an online environment for students that worked collaboratively and those that worked individually.

Another instrument developed for measuring perceived learning was designed to measure three specific dimensions of learning – cognitive, affective, and psychomotor (Rovai et al., 2009). The CAP Perceived Learning Scale was developed for use in higher education settings and has been implement in both face-to-face and online settings. For example, the CAP Perceived Learning Scale was used for comparing students' perceived learning via electronic books versus traditional hard copy books (Rockinson-Szapkiw, Courduff, Carter, & Bennett, 2013) and examining students perceived learning as a result of blogging in an education course (Top, Yukselturk, & Inan, 2010).

Others have gauged perceived learning with a variety of techniques. Reychav and Wu (2015) used perceived understanding for measuring learning impact. In this case, perceived understanding was measured using a dichotomous scale that included statements about the subject matter in which students stated whether they agreed or not. This scale was modified from a questionnaire aimed to measure the perceived teaching quality in higher education (Byrne & Flood, 2003). Ibabe and Jauregizar (2010) quantified students' perceived learning by calculating the difference in students' final perception of their knowledge of a topic and their initial perception. Perceived learning was measured in a statistics course comparing different models of collaborative testing;

students were questioned whether collaborative testing aided them in understanding statistical ideas (Eastridge & Benson, 2020).

2.3.3 Statistical Knowledge

Many have used course achievement or academic performance to measure students' knowledge of statistics. In addition to those mentioned previously (Summer et al., 2005; Lu & Lemonde, 2013), McIntyre (2020) measured gains in statistical content knowledge after exam review activities using a self-developed multiple-choice instrument. Bude´, Imbos, van de Wiel, and Berger (2011) created an instrument consisting of ten questions involving statistical hypothesis testing. It was found to have high interrater agreement but has not been used by other researches. Also, the questions focus on a specific statistical topic and therefore, may not be an adequate way of measuring statistical knowledge. Along with using course achievement for measuring learning, Campbell and Taylor (2019) administered a Pre-Semester Knowledge Assessment at the beginning of a research methods course that followed an introductory statistics course to investigate the degree to which students retained statistical knowledge.

Several instruments have been designed with the goal of measuring statistical understanding. The Comprehensive Assessment of Outcomes in Statistics (CAOS) is the one that has been mostly widely used in the literature. The audience of the CAOS is students that have completed any college-level introductory statistics course, and it focuses on conceptual understanding of statistics rather than techniques and calculations (delMas, Garfield, Ooms, & Chance, 2007). The COAS has been administered in a variety of settings. Hannigan, Gill, and Leavy (2013) examined pre-service secondary teachers' conceptual knowledge of statistics using CAOS after taking an introductory statistics course. Bowen, Chingos, Lack, & Nygren (2013) calculated CAOS gains to evaluate student learning in a face-to-face statistics course compared with a hybrid course. The COAS has also been used in online statistics courses for comparing student learning when using two different methods of collaborative tests (Bjornsdottir et al., 2015).

Two other instruments that have been developed to measure student learning of statistics are the Statistics Concepts Inventory (SCI) and the Levels of Conceptual Understanding of Statistics (LOCUS). The SCI sought to assess statistical understanding. It has primarily been used in calculus-based statistics courses and with engineering majors (Stone et al., 2003; Allen, 2006) and has not been widely implemented. The primary audience for the LOCUS is students in grades 6 through 12 (Whitaker, Fot, & Jacobbe, 2015), though it has been applied in introductory statistics courses at the college level (Jacobbe, Whitaker, Case, & Foti, 2014). Bolch and Jacobbe (2019) incorporated items form the LOCUS to assess students' graphical comprehension in an introductory statistics course. Dahlstrom-Hakk and Alstad (2019) used items from both the SCI and LOCUS to determine the instruments' effectiveness in assessing conceptual understanding of statistics in students with disabilities.

The COAS, SCI, and LOCUS were all written for different audiences; however, both the COAS and LOCUS instruments evaluate conceptual understanding of statistics. COAS was the most suitable instrument for measuring students learning gains in statistical knowledge for the current study since the population of interest consists of introductory statistics students.

2.4 Conceptual Framework

A key element in collaborative learning is interdependence; collaborative groups have been defined as having the highest level of interdependence (Graham & Misanchuk, 2004). In the proposed study this interdependence will take place in a social online environment through the use of synchronous video-based virtual meetings. Consequently, the study will be framed using the social interdependence theory (Johnson & Johnson, 1989). Using social interdependence theory as a conceptual framework offers a guide for how collaborative learning is best structured, modified for specific educational settings, and practiced for a variety of issues (Johnson & Johnson, 1998). Social interdependence theory exists at the intersection of "theory, research, and practice. The premise of the theory is that the way in which goals are structured determines how individuals interact, which in turn creates outcomes" (Johnson, 2003, p. 934). Social interdependence theory is rooted in the work of Lewin (1935) and Deutsch (1949). Lewin maintained that interdependence was essential when students work together and any changes to a single group member influences the entire group. Deutsch was the first to articulate the theory of social interdependence and stated that interdependence could be positive, negative, or nonexistent. Social interdependence theory is externally valid and generalizable given that it has been applied in a variety of settings using diverse procedures (Johnson, 2003).

When framing a study around social interdependence theory one must consider how the goals are formed and how that structuring establishes the way in which learners interact with one another. Goals can be structured such that they create positive, negative, or no interdependence. When positive interdependence exists, students believe that their goals can be accomplished if and only if the group accomplishes its goals. This type of interdependence creates promotive interaction. Learners support their group members and help make one another's learning possible when there is promotive interaction. When negative interdependence occurs, learners view that when one individual attains their goal then all others within the learning environment will fail to reach theirs. This type of interdependence produces oppositional interaction. Oppositional interaction creates competition among students as they discourage and create learning barriers for others. When there is no interdependence students work individually and reaching their goals is unrelated to whether or not their peers reach theirs. Without interdependence learners have no interaction with one another (Johnson & Johnson, 2002b). These types of interdependence and interactions then affect the outcomes including effort to achieve, relationships, and psychological (see Figure 2.2). Positive interdependence/promotive

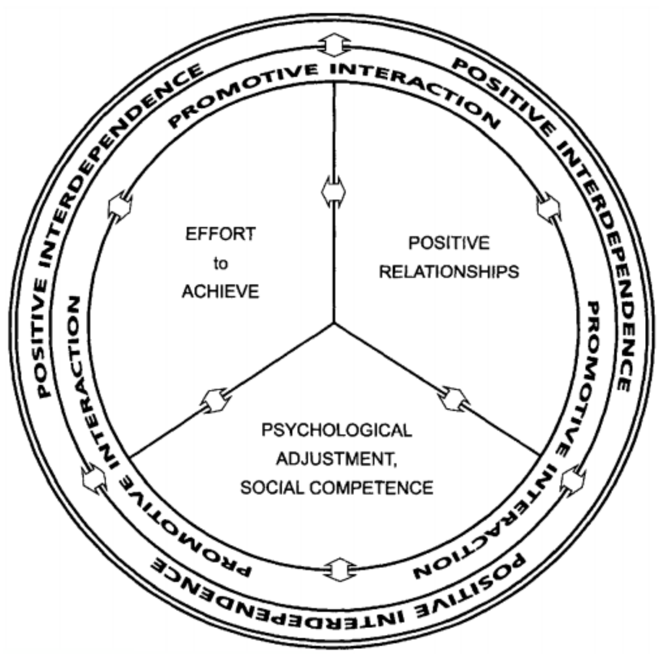


Figure 2.2 Social Interdependence Theory Outcomes (Johnson & Johnson, 1989)

interaction often results in high effort to achieve, positive relationships, and psychological health. Negative interdependence/oppositional interaction typically results in low effort to achieve, negative relationships, and psychological illness. Finally, when there is no interdependence, and hence no interaction, learners tend to have low effort to achieve, no relationships, and psychological pathology (Johnson & Johnson, 1998). In addition to positive interdependence and promotive interaction, social interdependence theory states individual accountability, social skills, and group processing are necessary for effective groups (Johnson & Johnson, 1989).

Social interdependence theory has been shown effective when applied in university settings (Johnson & Johnson, 2002b) and have been applied in online environments (Peterson, Beymer, & Putnam, 2018). By situating this study in the theory of social interdependence it was predicted that learners that worked collaboratively would have higher achievement than learners that worked individually. The study aimed to verify this claim.

CHAPTER 3. METHODOLOGY

This study examined the influence collaboration has on student learning in an asynchronous online introductory statistics course. The influence of collaborative learning was explored among all participants but also among lower performing students. This has not been studied in an online statistics course and fills a gap in the literature. Lower performing students have been less successful in online courses than they are in face-to-face courses. This study provides a collaborative model that educators and researchers may use in online courses to be built upon with the objective of improving student success, which will increase the likelihood they will complete their degree program (Tinto, 1993).

This investigation followed a quasi-experimental, quantitative design. Cen, Ruta, Powell, Hirsch, and Ng (2016) asserted that there is a lack in quantitative evidence in supporting collaborative learning. They defend that this may be partly caused by the struggle to represent formal knowledge quantitatively. This study aimed to do so by measuring learning in three different ways: academic achievement, perceived learning, and statistical knowledge. Using social interdependence theory as the framework for this study guided the way in which learning goals were defined and how groups interacted. This then guided the outcomes and in this study those outcomes were measured in multiple ways.

3.1 Setting and Participants

The population of interest for this study was students enrolled in an online asynchronous introductory statistics course at a medium sized public university located in the mid-south serving primarily undergraduate students. Due to the nature of the research, students enrolled in the two sections of the course taught by the researcher during the Spring 2022 semester were invited to participate in the study. The researcher has taught multiple sections of the course in various formats over the span of eight years. In addition, the researcher first taught an online course five years ago and has been teaching primarily online for three years. The combined enrollment of the course after the add/drop deadline was 106 students, and there were 94 students enrolled in the courses at the end of the semester. Of these students, 33 agreed to participate in the study. However, two of the participants did not complete any assessments or surveys and were excluded from the data analysis. Ultimately, data from 31 participants was utilized. Participants' demographic data were accessed from the university's database and self-reported by participants. Descriptive demographic statistics for the two sections are summarized in Table 3.1. The course is required for a majority of students at the university and those

Table 3.1 Group Demographics

	Control	Treatment
Sample Size	20	11
Percent of Female	85%	72.7%
Percent of Underrepresented Minorities	20%	9.1%
Percent of First-Generation Students	55%	36.4%
Mean Age	22.90	26.82
Mean Number of Prior Online Courses	4.80	6.27
Mean Number of Credit Hours Attempted Spring 2022	12.05	13.00
Mean Number of Cumulative Credit Hours Completed	68.60	89.00
Mean GPA	3.28	3.38
Mean Math ACT Score	22.78	22.73
Mean Reading ACT Score	24.06	25.90
Mean Hours Worked per Week	25.15	24.35

that are not required to take it may choose to do so in order to satisfy a general education requirement. Thus, there were a wide range of majors represented in the study. In general, the two sections were fairly similar in composition. Students must be *college ready* as defined by the Kentucky Council of Postsecondary Education in both mathematics and reading to place into the course. Otherwise, students must take prerequisite courses in mathematics and English or reading prior to taking the course.

Topics covered in the course included graphical and numerical summaries, normal distributions, statistical inference for one and two variables (categorical and quantitative), and simple linear regression. Students had the option to take the course in a traditional face-to-face format or online. Participants self-selected into one of the two sections assigned to the researcher during the spring of 2022 during the traditional 16-week semester. The two sections of the course appeared identical when the students registered for the course. Students in one section were used as the control group (no collaborative assignments) and students in the other section were the treatment group (collaborative assignments included).

3.2 Instrumentation

Three instruments were employed in order to measure student learning. Learning was measured by observing the demonstration of knowledge proficiency in the topics that were being studied (Johnson & Johnson, 1991), participants' perceptions of their learning (Alavi, 1994), and by evaluating the gain in knowledge – the central method in the literature for measuring collaborative learning (Dillenbourg, 1999). All these concepts of learning worked together to create an in-depth representation of their knowledge. It has been argued that individual learning should be measured when examining collaborative learning.

> Individual cognitive systems do not learn because they are individual, but because they perform some activities (reading, building, predicting, etc.) that trigger some learning mechanisms (induction, deduction, compilation, etc.). Similarly, peers do not learn because they are two, but because they perform some activities that trigger specific learning mechanisms (Dillenbourg, 1999, p. 6).

Hence, participants completed each of the assessments meant to measure their learning individually.

The construct of student learning was operationalized using students' academic achievement, perceived learning, and statistical knowledge. Single measures rarely completely describe a concept being inspected and the use of multiple measures allowed for an expanded understanding (Meyers, Gamst, & Guarino, 2006). Therefore, three instruments were implemented for measuring student learning. Academic achievement was measured by students' performance on a cumulative final exam. Perceived learning was measured using Alavi's (1994) Perceived Learning Scale. Statistical knowledge was measured using the difference in participants' pre- and post-test scores on the Comprehensive Assessment of Outcomes for a first course in Statistics (delMas et al., 2007).

It has been defended that more than one instrument should be used to measure a concept (Webb, 1966). There are many advantages to including multiple instruments for measuring learning outcomes. Measuring learning using different types of methods (demonstration of course topics, self-reported, and learning gains) supply different information related to student learning. Including multiple measures offers fuller, detailed data regarding students' response to the intervention of collaborative learning (Warner, 2008).

3.2.1 Academic Achievement

Academic achievement was measured using final exam grades. It was incorporated as a learning measure because it provided an opportunity for participants to make their knowledge of the course material known. The final exam was cumulative and potentially accessed all of the topics covered in the course. This included introductory definitions, summarizing categorical data, normal distributions, the sampling distribution of the sample proportion, hypothesis tests and confidence intervals for a proportion, chi-square tests, summarizing quantitative data, the sampling distribution of the sample mean, hypothesis tests and confidence intervals for a mean as well as two sample inferences for a mean, simple linear regression, and correlation. One version of the final exam is provided in Appendix A. Participants were permitted use of a formula sheet (see Appendix B) while taking the final exam. Exam grades and course grades have frequently been used to measure academic achievement (Hiltz & Wellman, 1997). The final exam – rather than the individual exams – was chosen to measure academic achievement since it assessed topics from the entire course. The researcher was the primary grader of the exams as the instructor of the course in which the participants were enrolled. Therefore, an external expert also graded four randomly selected exams using the same rubric for establishing interrater reliability. Consistency estimates were sufficient since summative scores were used for determining each participants' grade (Oakleaf, 2009). There was high consistency between the scores of the researcher and external expert (r = 0.99, p = .009). Other researchers have used the collaborative assignments themselves as the measure for academic achievement and found significant differences between the scores for students completing the assignments collaboratively versus individually (Kurucay & Inan, 2017). However, this study sought to determine if the learning that developed collaboratively extended beyond the collaborative setting.

3.2.2 Perceived Learning Scale

Perceived learning, or self-reported learning, has been shown to be a valid measure of student learning (Pike, 2011). Perceived learning was incorporated as one of the learning measures because it allowed for student perceptions of their learning to be uncovered. Alavi (1994) developed a perceived learning scale modified from Hiltz's (1988) questionnaire evaluating the effectiveness of online courses. Alavi's perceived learning scale contains three separate learning scales – perceived skill development, self-reported learning, and learning interest. The first two of these scales were included in the perceived learning scale for the current study since they more directly measured the desired construct. Some items were reworded with the appropriate context. The perceived learning scale used is available in Appendix C. The perceived learning scales when originally developed were found to have acceptable reliabilities; the perceived skill development scale had a reliability of 0.91 and the self-reported learning scale had a reliability of 0.83. Internal consistency of the perceived learning scaled used for the current study was analyzed, and Cronbach's alpha for this specific sample was 0.90 indicating a high level of reliability.

Though it was developed some time ago, Alavi's scale continues to be implemented in studies for measuring perceived learning in both online and traditional formats (Chen & Jang, 2010; Kurucay & Inan, 2017; Chen, Jones, & Xu, 2018; Bravo, Catalán, & Pina, 2019) and an updated scale intended for measuring the desired learning outcomes with perceived learning or self-reported learning has not yet been created. After a review of the CAP Perceived Learning Scale (Rovai et al., 2009), it was determined that some of the items were not appropriate for the current study. There was a focus on other learning dimensions (namely, affective and psychomotor), which are beyond the scope of this study.

3.2.3 Comprehensive Assessment of Outcomes for a First Course in Statistics

The Comprehensive Assessment of Outcomes for a first course in Statistics (CAOS) is a 40-item multiple choice assessment which measures students' statistical reasoning. The CAOS was selected as the final instrument for evaluating student learning because it provided a means for quantifying participants' gain in statistical knowledge through the use of a pre- and post-test. The CAOS includes questions that students should be able to answer after completing any introductory statistics course. The assessment was developed "to identify areas where students do and do not make significant gains in their statistical understanding and reasoning" (delMas et al., 2007, p. 30). The CAOS items assess students' understanding of statistical topics such as data collection and design, descriptive statistics, graphical representations, normal distributions, bivariate data, probability, sampling variability, confidence intervals, and tests of significance. The CAOS was used for measuring students' learning of statistics because it is best suited for the audience in which the study was investigating. Access to the CAOS instrument may be requested here.

The CAOS was found to have reasonable internal consistency for students enrolled in a post-secondary introductory statistics course (delMas et al., 2007). The Cronbach's alpha from the sample used by delMas et al. (2007) was 0.82. The instrument was also found to be valid; a group of 18 experts had a 94% agreement that the CAOS measures essential learning outcomes in statistics. 100% of the raters agreed that it "measures outcomes for which I would be disappointed if they were not achieved by students who succeed in my statistics courses" (delMas et al., 2007, p. 31). In addition to the CAOS being a reliable and valid assessment for measuring students' statistical reasoning in statistics, it has previously been used for measuring student learning in online introductory statistics courses (Hahs-Vaughn et al., 2017; Bjornsdottir, Garfield, & Everson, 2015).

3.3 Intervention

The treatment used in this study was the incorporation of collaborative assignments. Prior to the start of the course, one section was randomly assigned as the control section and the other section was the experimental section. Students in the control group did not complete collaborative assignments, and students in the experimental section were required to complete collaborative assignments. In order to maintain as much similarity as possible in the two sections – other than study treatment – the following were identical across both sections: course organization and information provided in the LMS, required materials, lecture videos and corresponding guided notes (partial notes that students completed while watching lecture videos), online homework assignments, exams with multiple versions of questions, and grading procedures.

Students in the experimental section completed seven collaborative assignments with a small group of classmates. These students met virtually during an assigned time based on their availability as provided to the instructor. Students were required to have their webcams and microphones for the duration of the meeting. Students in the control group completed an identical assignment individually. A sample collaborative assignment is available in Appendix D. The 21st Century Learning Design (21CLD) rubric (ITL Research, 2012) was considered when the collaborative assignments were created; each assignment was constructed so that students worked together, had a shared responsibility, made decisions together, and worked interdependently.

3.3.1 Collaborative Assignments

Though there are numerous benefits of implementing collaboration in online courses, collaborative assignments do not come without challenges. Graham and Misanchuk (2004) give three aspects to consider when incorporating group work in an online environment: creating groups, structure of the learning activities, and facilitation of the groups (Figure 3.1). These three elements were taken into consideration when

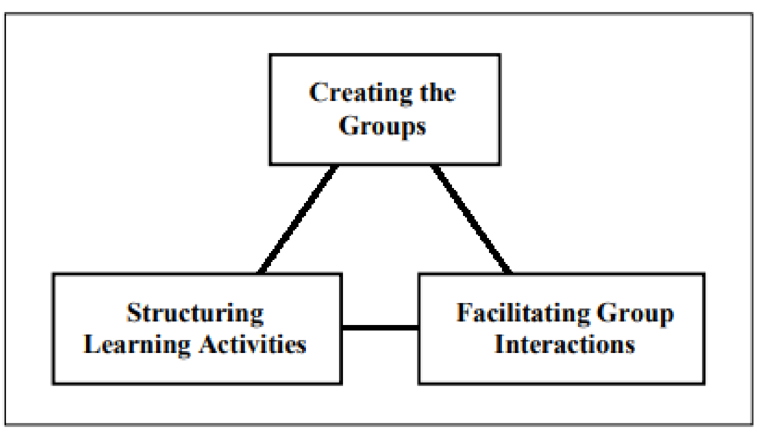


Figure 3.1 Elements in Creating Effective Learning Groups (Graham & Misanchuk, 2004)

designing the collaborative assignments. When learners collaborate, there is an expectation that they will interact in some way, but there is no guarantee that will happen (Dillenbourg, 1999). Therefore, in designing the intervention the goal was to increase the likelihood of that taking place.

3.3.1.1 Creating Groups

When creating groups both size and composition of the group were taken into consideration. Researchers suggest that the "smaller the better" when it comes to collaborative groups (Johnson, Johnson, & Holubec, 1994). There has not been consensus on the best group size. For example, Al Mulhim and Eldokhny (2020) found that larger groups – 7 or 8 students – scored significantly higher than smaller groups – 3 or 4 students – on an achievement post-test. Conversely, Johnson, Johnson, and Holubec (2020) recommend groups of two or three. Further, Enu, Danso, and Awortwe (2015) found no significant difference in mathematics achievement between groups of size three, four, and five students. Due to the fully asynchronous nature of the course, there was not a common meeting time. Groups were assigned based on students' availability to avoid logistical issues. At the beginning of the course students completed a poll stating their availability among options provided by the researcher. In taking all this in consideration 14 groups each with four students were created.

Homogeneous and heterogeneous groups both come with benefits and challenges. Heterogeneous groups in terms of gender, skills, and grades have been found more beneficial than homogeneous groups (Cen, Ruta, Powell, Hirsch, & Ng, 2016). Though student voice can be a concern in heterogeneous groups. Karpowitz, Mendelberg, and Shaker (2012) observed a disparity in voice and authority between women and men in mixed gender groups. However, when decisions were required to be unanimous among groups with few women or when decisions were required to be a majority among groups with many women this gap disappeared. Tinzmann, Jones, Fennimore, Bakker, Fine and Pierce (1990) identified heterogeneous groups as one of the characteristics of a collaborative group. Students' CAOS pre-test scores were also used for making heterogeneous groups when possible. When heterogeneous groups were not feasible due to students' schedules, McInnerney and Roberts (2004) defended that students may learn even when the group composition is not ideal. Groups were created with as much heterogeneity as possible, though there was little control over the group composition since groups were created based on the time(s) selected by the participants. Students were placed in at time slot based on their availability; there were at least two groups meeting at a given time. This allowed for groups to be collapsed as needed. This was done when groups only had one or two students in attendance.

3.3.1.2 Structure of the Learning Activities

When structuring collaborative assignments Graham and Misanchuk (2004) urge educators to create individual accountability and a high level of interdependence. Student accountability has been described as a component that educators must consider when designing collaborative assignments (MacGregory, 1994). The intervention established individual accountability in multiple ways. Students had requirements to complete prior to their group meetings. The requirements included viewing lecture videos and completing corresponding guided notes associated with the assignment. Each group member was also required to fully attempt all individual pre-work questions. Researchers have found that pre-work tasks positively influence collaborative learning (Koszalka, Pavlov, & Wu, 2021; Cox, 2015). The pre-work questions ensured students had finished the lecture content and served as a starting point for discussion during the collaboration. Questions on the individual pre-work included partial and/or full examples that were then finalized with their group. Learners posted their pre-work to their group's discussion board and were unable to see others' responses until they had made their own post. Students were asked to read through their group members' posts prior to their group meeting. This aided in the prevention of "freeloaders" in the group setting (Shibley & Zimarro, 2002)

Graham and Misanchuk (2004) define collaborative groups as having the highest level of interdependence (see Figure 2.1). Requiring all students in a group to work together on all parts of an assignment creates a high level of interdependence, as opposed to taking a *divide and conquer* approach which creates a low level of interdependence. Learners often have difficulty establishing interdependence (Dirkx & Smith, 2004). The intervention sought to achieve the highest level of interdependence. During their group meetings participants discussed their responses to the assignment pre-work and completed the remaining portions of the assignment collaboratively. Each student in the group answered the questions on their own paper while discussing the assignment with their group mates. All students submitted their work at the conclusion of the meeting. One submission from each group was randomly selected for grading. The grade earned on that submission was the grade earn by the entire group. Knowing that their group members' success depend on them can be a beneficial motivator for students (Kohn, 1986).

3.3.1.3 Facilitation of the Groups

Communicating effectively in online collaboration is essential for the group's success. Anderson (2004) advocates the use of a self-introduction tasks for students "to develop a sense of trust and safety" and that without it "learners will feel uncomfortable and constrained in posting their thoughts and comments." Students should devote time getting to know their group members for optimizing the collaboration (Nooijer, Schneider, & Verstegen, 2020). Learners in an argumentative essay writing course that were given explicit socializing tasks prior to learning activities had significantly better learning outcomes than those that had implicit socializing tasks (Jiang & Zhang, 2020). Giving students an opportunity to introduce themselves and become comfortable with their group members creates an environment where learning can take place (Rovai, 2002). Therefore, space was set aside during the first group interactions that allowed participants to introduce themselves.

The facilitator of the groups must ensure groups have the necessary skills needed to make decisions and come to a consensus (Graham and Misanchuk, 2004). Participants were encouraged to talk through their work, rather than checking their work with their group members after completing a problem. The researcher was available – though in a separate virtual meeting space – during all group meetings to answer questions and check in as needed. The teacher has the responsibility of being accessible and providing feedback during online collaboration (Nooijer et al., 2020). Group interaction is strengthened when the instructor interacts with the learners (Hernández-Sellés et al., 2019). Though, it is important that the instructor not act as the final authority so as to not hold back the growth of the collaborative process (Dirkx & Smith, 2004). While in the meeting space the researcher examined whether or not all group members were participating and contributing to the assignment and if not supported students in doing so.

> Structures can be constructed which will support group collaboration. However, they can only facilitate the desired behavior, not produce it. For the group to adapt a structure of interaction that is collaborative in nature, the instructor must mold, model, and encourage the desired behavior, and the students must be able and willing to participate regularly. (Hiltz, 1998, p. 7)

3.4 Data Collection

At the beginning of the semester all students enrolled in the course were invited to participate in the study. Adult students received a digital informed consent form detailing the components of the study. Minor students were asked to provide an email address of a parent or guardian in which a parental permission form could be sent. After the parental permission form was completed minor participants received a digital informed assent form detailing the components of the study. Students were requested to complete the appropriate form stating whether or not they consented/assented to their data being used prior to the data collection. Consent/assent forms were maintained by a faculty member at the researcher's institutions that was not involved in the study. All students enrolled in the course were required to complete a pre-survey containing a few demographic questions and the CAOS items with the intent of assessing their statistical reasoning. This was completed within the course Learning Management Systems as part of the course attendance requirements. Students completed a post-survey at the end of the course. Within the post-survey students once again answered the CAOS items to measure the growth in their statistical reasoning. The perceived learning scale was included in the post-survey as well. Students earned course participation points for completing the end-of-course survey.

3.5 Data Analysis Approach

In this study learning was measured using three outcome variables: academic achievement, perceived learning, and gain in statistical knowledge. Academic achievement was measured using the score students earned on the final exam. Perceived learning was quantified using the mean score on the eight Likert items – using a 1 to 5 rating – from the perceived learning scale. Gain in statistical knowledge was calculated using the difference in each student's post- and pre-CAOS scores. In order to answer the research question of what influence does collaborative learning have on student learning in an asynchronous online introductory statistics course, the data collected from this study was analyzed using a variety of quantitative methods.

3.5.1 Comparing Learning Measures Between Groups

In order to determine the degree student learning differs among students that work collaboratively in an asynchronous online introductory statistics course compared with students that work individually in the same setting, multivariate analysis of variance (MANOVA) was executed. The means of the learning measures between the treatment and control groups were compared. MANOVA inference procedures assume all of the dependent variables are measured at the interval or ratio levels. Likert scales assume equal distance between response, though the data is truly ordinal in nature. However, numerous researchers have treated Likert data as interval or ratio in statistical analyses.

This process is broadly viewed as “acceptable, appropriate, and quite useful” (Meyers, Gamst, and Guarion, 2006, p. 23). Post hoc analysis was planned using discriminant function analysis had significant differences in the two groups been found.

The dependent variables of academic achievement, perceived learning, and statistical knowledge were selected to measure student learning and were expected to be linearly related. MANOVA assumes that each pair of dependent variables within each of the groups have a moderate correlation. This was not found with the dependent variables from this study, though it was believed that would be the case. Therefore, three separate independent sample *t*-tests with a Bonferroni adjustment were also implemented for comparing the control and treatment groups for each of the learning measures.

3.5.2 Comparing Learning Measures Between Groups Among Lower Performing Students

Next, the degree student learning differed among lower performing students that work collaboratively compared with lower performing students that work individually was investigated. It has been observed that lower performing students have significantly lower grades in online course than they do in face-to-face courses (Cavanaugh & Jacquemin, 2015; Lu and Lemonde, 2013). Further, it has been detected that lower performing students benefit more from collaborative learning than higher performing students (Han et al., 2015; Saner et al., 1994). Student were classified as lower performing if their course grade was at or below the median for their class section. Lu and Lemonde (2013) divided students into “lower” and “higher” groups in a similar way. Also, the decision to split the sections in this way is backed by the notion that this subset of students has been reported to have lower course grades in online courses.

The correlation assumption of MANOVA was first checked for the lower performing participants, since the lack of correlation in the dependent variables existed among all participants. There was also an absence of correlation in the lower performing participants' data. Consequently, three separate independent sample *t*-tests with a Bonferroni adjustment were performed to compare the learning measures of the lower performing students in the control and treatment groups.

3.5.3 Regression Models for Student Learning

Finally, this research desired to establish the degree collaborative learning contributed to student learning in an asynchronous online introductory statistics course. Regression analysis was used to address this research question. Regression analysis is a tool used to investigate a variety of research questions; the main goal in any regression analysis is examining the relationship between a dependent variable and independent variables (Tabachnick & Fidell, 2001). To determine the degree collaborative learning contributed to student learning in an asynchronous online introductory statistics course hierarchical multiple regression analysis was performed. Hierarchical methods were preferred since models constructed using stepwise methods may not include the desired group variable. Though stepwise regression was utilized for initially selecting some important variables that may not have been identified as such in the literature (Mendenhall & Sincich, 2012). The independent variables which were considered when building the regression models included: group (treatment or control), CAOS pre-test score, number of prior online courses, age, gender, number of assignments completed, cumulative credit hours complete, credit hours attempted during the current semester, average hours of work per week, college GPA, Math ACT score, Reading ACT score, whether or not the student is an underrepresented minority, and whether or not the student is a first-generation college student. A separate model was fitted for each of the following dependent variables: academic achievement, perceived learning, and statistical knowledge. This approach was also used by Bjornsdottir et al. (2015) when examining how two different types of collaborative tests influenced students' learning in an online statistics course.

CHAPTER 4. ANALYSIS AND RESULTS

This quasi-experimental quantitative study aimed to determine what influence collaborative learning has on student learning in an asynchronous online introductory statistics course. Mean scores of each learning measure were compared for the two groups to examine the degree to which student learning differs for students that work collaboratively versus students that work individually. A similar procedure was conducted for judging the differences in learning among lower performing students. Finally, regression analysis was completed with the goal of quantifying the contribution collaboration has on student learning.

4.1 Comparison of Learning Measures Between Group

First Research Question**:** *To what degree does student learning differ among students that work collaboratively in an asynchronous online introductory statistics course compared with students that work individually in the same setting?*

A one-way MANOVA procedure was conducted examining the influence of group (treatment or control) on academic achievement, perceived learning, and statistical knowledge scores. A MANOVA procedure was implement since multiple dependent variables were being compared between groups. This procedure is often beneficial because it can offer more information on student learning with multiple measures, affords some control over probability of committing a Type I error, and takes into account the intercorrelation between dependent variables which are missing when multiple *t*-tests are performed (Meyers et al., 2006). However, the dependent variables in this study did not possess the desired correlations for a MANOVA though it was assumed they would. Hence, the MANOVA analysis was followed with multiple independent samples *t*-tests.

4.1.1 Multivariate Data Screening

Multiple analysis of variance (MANOVA) was conducted to compare learning among participants that completed collaborative assignments against those that completed the assignments individuals. Missing data was first addressed and then the data was screened to ensure a MANOVA procedure was appropriate. There are several assumptions that must be met in order for a MANOVA to yield valid results; the assumptions must consider the multivariate nature of the data. The procedure requires a sufficient sample size, is sensitive to multivariate outliers, the dependent variables must have multivariate normality and have a moderate correlation between each pair of the dependent variables, and there must be homogeneity of covariance matrices for each dependent variable across groups.

4.1.1.1 Missing Data

Missing data can be problematic when analyzing data using MANOVA procedures. Four out of the 33 students that agreed to participate in the study were missing values for at least one of the dependent variables. This missing data was handled as follows: Two of these participants did not complete any of the assessments and surveys. Therefore, these two cases were excluded from the analysis. The two remaining participants with missing data completed at least one of the items. An imputation procedure was implemented for these two cases. The sample size was relatively small and an imputation procedure allowed for the data to be preserved. Mean substitution was the imputation procedure selected; this practice is the imputation procedure used most frequently and is the most conservative (Meyers et al., 2006).

4.1.1.2 Sample Size Requirements

MANOVA analysis typically requires a larger sample size than what is needed when there is a single dependent variable. Generally, the larger the sample the better, though a minimum requirement for MANOVA is that the number of cases in each cell is more than the number of dependent variables (Meyers et al., 2006). In the present study, four or more observations were required in each cell.

4.1.1.3 Outlier Detection

It was important to observe whether or not multivariate outliers were present in the data, since MANOVA is sensitive to outliers. The data were screened for multivariate outliers by calculating the Mahalanobis distance for each case (Mahalanobis, 1936). The maximum Mahalanobis distance was found to be 8.759. This was below 16.266, the threshold when there are three variables. Hence, no multivariate outliers were detected.

4.1.1.4 Multivariate Normality

MANOVA procedures require simultaneous normality of the dependent variables. Multivariate normality can be assumed for samples containing at least 20 elements in each cell (Tabachnick & Fidell, 2001). However, the sample in this study did not meet this criterion and thus, it was necessary to establish multivariate normality. One way to access for multivariate normality is by using Mardia’s statistics (Mardia, 1970). The expected values for Mardia’s statistics in a multivariate normal distribution are zero for skewness and $p(p + 2)$ for kurtosis, where p represents the number of dependent variables

(Cain, Zhang, & Yuan, 2017). With three dependent variables – as in the current study – the expected value for Mardia's kurtosis is 15. Mardia's skewness and kurtosis were calculated as well as the corresponding test statistics and p-values (see Table 4.1). Multivariate normality can be assumed based on this information.

Table 4.1 Mardia's Multivariate Normality Screening

	Mardia's Statistic	Test Statistic	p-value
Skewness	0.7706	$\chi^2 = 3.98$	.9482
Kurtosis	14.67	$z = -0.17$	.8663

4.1.1.5 Correlations Between Dependent Variable

Another assumption of MANOVA is that there is a moderate correlation between each pair of dependent variables within each of the groups. This condition can be assessed using scatterplots and/or Pearson's correlation. Scatterplots of normally distributed variables that are linearly related will appear elliptical (Meyers et al., 2006). The data was previously screened for multivariate normality. Thus, an elliptical form was expected for demonstrating a linear relationship between the dependent variables. Figure 4.1 shows the matrix scatterplot for the dependent variables among the two groups – control and treatment. Though not all the scatterplots appeared elliptical in form, it was

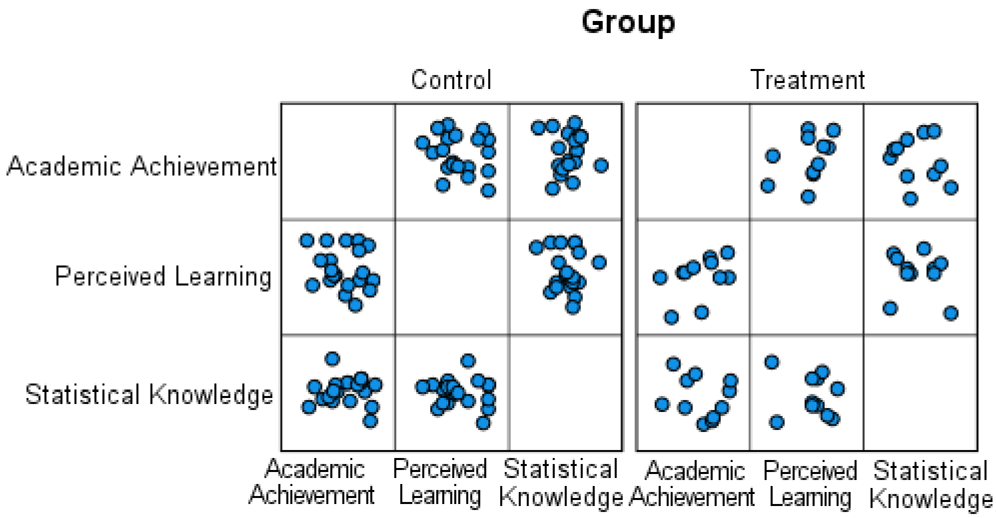


Figure 4.1 Matrix Scatterplot for Dependent Variables

important to note that there did not appear to be any non-linear relationships between the variables. Next, correlations between each pair of dependent variables within each of the groups were calculated. The correlations should be between 0.3 and 0.7 to indicate a moderate linear relationship (Ratner, 2009). The variables should not be highly correlated to avoid multicollinearity; high correlations may suggest the variables are measuring the same detail and therefore, both variables are not necessary. The correlations for the two groups were calculated (see Tables 4.2 and 4.3). Several of the correlations were less than

Table 4.2 Correlations between Dependent Variables – Control Group

	Academic Achievement	Perceived Learning	Statistical Knowledge
Academic Achievement	1.000		
Perceived Learning	-.184	1.000	
Statistical Knowledge	-.009	-.111	1.000

Table 4.3 Correlations between Dependent Variables – Treatment Group

	Academic Achievement	Perceived Learning	Statistical Knowledge
Academic Achievement	1.000		
Perceived Learning	.412	1.000	
Statistical Knowledge	-.209	-.175	1.000

0.3 and hence, did not support a linear relationship between the variables. The power of a MANOVA procedure is reduced when the dependent variables are not linearly related (Tabachnick & Fidell, 2001). This was kept in consideration when the MANOVA results were interpreted.

4.1.1.6 Homogeneity

The final MANOVA assumption that was assessed was homogeneity of covariance matrices for the three dependent variables across the two groups. Violations of this assumptions result in more severe consequences when the size of the groups differ (Meyers et al, 2006) – as was the case in this study. The standard method for checking this homogeneity assumptions is by using Box's M test. This test was run producing a non-significant result, $F(6, 2740) = 0.84$, $p = .539$. Hence this assumption was met.

4.1.2 Multivariate Analysis of Variance Results

After the data were screened, a one-way MANOVA procedure was conducted examining the influence of group (treatment or control) on academic achievement, perceived learning, and statistical knowledge. The results of this analysis method were interpreted with caution since the dependent variables were not moderately correlated – though no non-linear relationships were present. In the sample used for this study, the mean scores on each of the learning measures were slightly higher for participants in the control group than they were in the treatment group (see Table 4.4). However, the MANOVA inference method found that there were no significant differences in these scores, $F(3, 27) = 0.874$, $p = .467$; Wilk's $\Lambda = .911$, partial $\eta^2 = .09$.

Table 4.4 Descriptive Statistics for All Participants

		Mean	SD
Academic Achievement	Control[a]	71.78	12.05
	Treatment[b]	68.60	19.66
Perceived Learning	Control	4.29	0.51
	Treatment	4.01	0.51
Statistical Knowledge	Control	10.34	16.57
	Treatment	7.5	15.29

[a] n = 20
[b] n = 11

4.1.3 Univariate Data Screening

A multivariate comparison was originally conducted since it was assumed that all the learning measures used – academic achievement, perceived learning, and statistical knowledge – would be correlated as they all quantified participants' learning in some fashion. However, this may not be the most appropriate approach since there were not moderate correlations between each pair of dependent variables within the two groups (Meyers et al., 2006). Instead, an alternate method was utilized for addressing the question of what influence does collaborative learning have on academic achievement, perceived learning, and statistical knowledge. Independent samples *t*-tests were conducted with an adjusted alpha level. To control for the likelihood of a Type I error the *t*-tests were run with a Bonferroni adjusted alpha of .05/3 = 0.017. Multivariate data screening was previously completed. Had there been an any violations of the assumptions the data would have been examined at the univariate level to determine where the issues lie. This was not the case and therefore, now a thorough examination of the dependent variables within each of the groups at the univariate level is necessary.

4.1.3.1 Outlier Detection

Boxplots of for each learning measure were created to compare participants' learning in the two groups. Figure 4.2 shows the boxplots of the three dependent

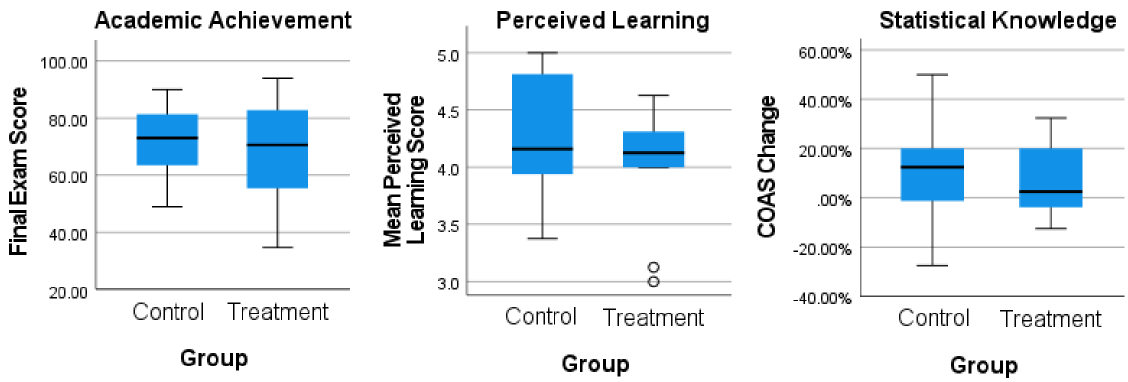


Figure 4.2 Boxplots of Dependent Variables

variables. Two outliers were detected among the treatment group for perceived learning. These two data points were standardized for further investigation. Their z-scores were found to be -1.73 and -1.97. A general recommendation is to consider cases beyond ± 2.5 standard deviations from the mean outliers (Hair, Anderson, Tatham, & Black, 1998). Hence, the assumption of no univariate outliers was satisfied.

4.1.3.2 Univariate Normality

The dependent variables – academic achievement, perceived learning, and statistical knowledge – within each group were assessed for normality by calculating the skewness, kurtosis, and Shaprio-Wilk's p-value for each (see Table 4.5). Some of the

Table 4.5 Normality Screening for Dependent Variables in Each Group

	Skewness	Kurtosis	Shapiro-Wilk (p-value)
Achievement – C	-0.22, z = -0.43	-0.95, z = -0.04	.498
Perceived Learning – C	0.13, z = 0.26	-1.09, z = -1.10	.123
Statistical Knowledge – C	-0.06, z = -0.11	1.31, z = 1.32	.429
Achievement – T	-0.31, z = -0.46	-0.97, z = -0.76	.710
Perceived Learning – T	-1.19, z = -1.80	0.79, z = 0.62	.039
Statistical Knowledge – T	0.25, z = 0.37	-1.33, z = -1.04	.467

skewness and kurtosis values were great than |1|; therefore, the corresponding z-scores for these are also given in the table. None of the z-scores were greater than |1.96| which would associate with a *p*-value less than 0.05 indicating a non-normal distribution (Cramer & Howitt, 2004). Further, lower alpha levels (.01 or .001) can be applied when working with small to moderate-sized samples when assessing normality (Tabachnick & Fidell, 2001). Hence, it is safe to assume the univariate normality is met.

4.1.3.3 Homogeneity of Variances

Levene's tests were conducted to assess for equal variances of the two groups for each dependent variable (see Table 4.6). Academic achievement had a significant result

Table 4.6 Levene's Test for Dependent Variables

	F(1, 29)	p
Academic Achievement	4.65	.039
Perceived Learning	0.51	.480
Statistical Knowledge	0.05	.828

when Levene's test was performed, indicating the unequal variances of final exam scores for the control and treatment groups. Therefore, a *t*-test with equal variances not assumed was executed for academic achievement. Perceived learning and statistical knowledge had non-significant results from Levene's test; *t*-tests with equal variances were conducted for these two dependent variables.

4.1.4 Independent Samples t-Tests Results

After the univariate data screening process, three independent samples *t*-tests were completed to compare student learning for the treatment and control groups (see Table 4.7). No significant differences were found in any of the learning measured. The

Table 4.7 Statistical Inference for Mean Difference (Treatment – Control)

	test statistic	p	95% CI	Cohen's d
Academic Achievement	$t(12.2) = -0.49$	.634	[-14.77, 8.43]	-0.21
Perceived Learning	$t(29) = -1.46$	.155	[-0.67, 0.11]	-0.55
Statistical Knowledge	$t(29) = -0.47$	.643	[-15.23, 9.55]	-0.18

p-values would have needed to be less than the Bonferroni adjusted alpha level of .05/3 = 0.017 to indicate significant difference in the means. These results agreed with the multivariate analysis of variance results previously reported.

4.2 Comparison of Learning Measures Between Groups Among Lower Performing Students

Second Research Question: *To what degree does student learning differ among lower performing students that work collaboratively in an asynchronous online introductory statistics course compared with lower performing students that work individually in the same setting?*

There were no significant differences found in the learning measures when all participants in the groups were compared. However, an additional goal of the research was to determine how collaboration influences the learning among lower performing students. Lower performing students often have lower grades in online course than they do in face-to-face courses (Cavanaugh & Jacquemin, 2015), yet benefit more from collaborative learning than higher performing students (Han et al., Capraro, & Capraro, 2015). Therefore, the learning measures for participants classified as *lower performing* were compared for the two groups. Any student whose course grade was below the median course grade for their section was classified as lower performing.

4.2.1 Correlations Between Dependent Variables for Lower Performing Students

Previously, comparing the learning measures among all students using multivariate analysis of variance was questionable due to the fact that not all of the dependent variables had a moderate linear relationship. Therefore, when comparing the learning measures among the lower performing students the correlations between each pair of dependent variables within each of the groups were first calculated (see Tables 4.8 and 4.9). Once again, the majority of these correlations were below the .3 threshold.

Table 4.8 Correlations between Dependent Variables – Lower Performing Control Group

	Academic Achievement	Perceived Learning	Statistical Knowledge
Academic Achievement	1.00		
Perceived Learning	-.43	1.00	
Statistical Knowledge	.41	-.14	1.00

Table 4.9 Correlations between Dependent Variables – Lower Performing Treatment Group

	Academic Achievement	Perceived Learning	Statistical Knowledge
Academic Achievement	1.00		
Perceived Learning	.25	1.00	
Statistical Knowledge	-0.46	-.17	1.00

Therefore, it was likely more appropriate to conduct simultaneous independent samples *t*-tests with a Bonferroni adjustment to address this research question.

Additionally, the sample size was reduced when limiting the analysis to participants identified as lower performing. In the control group, 30% (6 out of 20) of the participants were classified as lower performing. In the treatment group, 64% (7 out of 11) of the participants were classified as lower performing. It is worth noting that the difference in the proportion of lower performing students in the two groups was significant ($\chi^2 = 3.30$, $p = 0.0694$) which may have attributed the mean scores of the learning measures for the treatment group being slightly lower than the control group when comparing all participants.

4.2.2 Univariate Data Screening for Lower Performing Students

Prior to completing the *t*-test analysis, the data for each dependent variable within each group was screened at the univariate level to verify all necessary assumptions were met. The data must not have any extreme observations, be approximately normally distributed, and the two groups should have equal variance for each of the dependent variables.

4.2.2.1 Outlier Detection

The data were first graphically screened to determine if any outliers were present (see Figure 4.3). It appeared that there was one potential statistical knowledge outlier

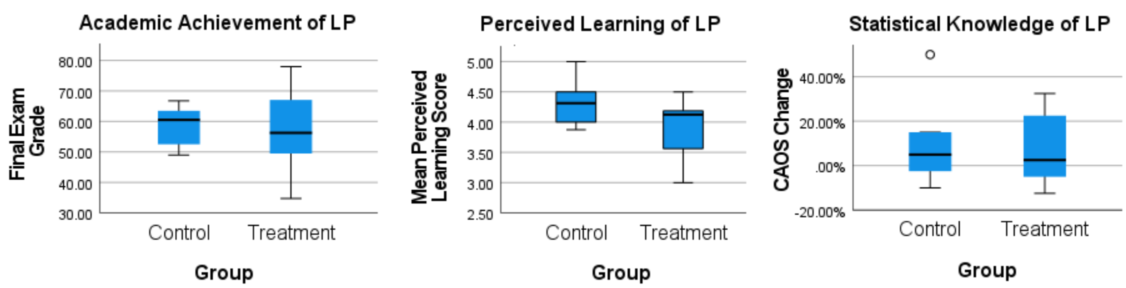


Figure 4.3 Boxplots of Dependent Variables Among Lower Performing Students

within the control group. This observation was standardized and calculated to be $z = 1.9$, which is within the |2.5| limit. Therefore, no extreme observations were detected.

4.2.2.2 Univariate Normality

Following the outlier screening, normality screening was performed. Skewness and kurtosis were calculated for each dependent variable within the two groups; Shapiro-Wilk's normality test was also conducted (see Table 4.10). None of the Shapiro-Wilk's

Table 4.10 Normality Screening for Dependent Variables – Lower Performing Participants

	Skewness	Kurtosis	Shapiro-Wilk (p-value)
Achievement – C	-0.42, z = -0.49	-1.65, z = -0.95	.526
Perceived Learning – C	0.68, z = 0.81	-0.22, z = -0.13	.582
Statistical Knowledge – C	1.55, z = 1.83	2.73, z = 1.57	.202
Achievement – T	-0.19, z = -0.24	-0.59, z = -0.37	.980
Perceived Learning – T	-0.92, z = -1.16	-0.85, z = -0.54	.092
Statistical Knowledge – T	0.21, z = 0.27	-1.82, z = -1.15	.461

p-values were significant; however, some of the skewness and kurtosis values were greater than |1|, so their standardized scores were also calculated. None of those were discovered to be greater than |1.96|. Hence, it was reasonable to assume that all the dependent variables for each of the groups were normally distributed.

4.2.2.3 Homogeneity of Variances

Lastly, the variances of the two groups were compared for each of the dependent variables using Levene's test (see Table 4.11). There were no significant differences and homogeneity of variances was assumed.

Table 4.11 Levene's Test for Each Dependent Variable – Lower Performing Students

	F(1, 11)	p
Academic Achievement	2.38	.151
Perceived Learning	0.88	.367
Statistical Knowledge	0.004	.950

4.2.3 Independent Samples t-Tests Results for Lower Performing Students

The scores on the learning measures were compared for the lower performing participants to determine the degree to which collaborative learning affected student learning. The sample means for all three dependent variables were slightly higher for the control group than the treatment group (see Table 4.12). Then independent samples *t*-tests with equal variances assumed were run to examine whether any of the mean differences were significant (see table 4.13). There were no significant differences in student learning among the lower performing students; this is similar to the findings for all participants.

Table 4.12 Descriptive Statistics for Lower Performing Students

		Mean	SD
Achievement	Control[a]	58.79	7.00
	Treatment[b]	57.45	14.87
Perceived Learning	Control	4.33	0.42
	Treatment	3.88	0.58
Statistical Knowledge	Control	10.42	21.36
	Treatment	8.21	17.66

[a] n = 6
[b] n = 7

Table 4.13 Statistical Inference for Mean Difference (Treatment – Control) for Lower Performing Students

	t(16)	p	95% CI	Cohen's d
Academic Achievement	-0.20	.844	[-15.98, 13.29]	-0.11
Perceived Learning	-1.61	.135	[-1.08, 0.167]	-0.90
Statistical Knowledge	-0.20	.842	[-25.99, 21.59]	-0.11

4.3 Regression Models for Student Learning

Third Research Question: *To what degree does collaborative learning contribute to student learning in an asynchronous online introductory statistics course?*

The final goal of this study was to determine the degree to which collaboration contributed to student learning. Hierarchical multiple regression analysis was performed to ensure the group level variable was included in the regression model as well as other important independent variables. It has been previously shown that group did not have a significant influence on participants' learning and will likely not be a significant predictor, but it will be included in the model in order to quantity the unique importance of the group in which participants were enrolled. Each of the regression models initially included significant predictors of the dependent variable, followed by the addition of the group level variable. The change in R-squared and the squared semipartial correlation of the group level variable were calculated after the group variable was included in the model to measure the unique impact collaborative learning had on the participants' learning.

The small sample size available in this study was considered prior to building the regression models. It has been recommended that the sample size required when testing individual independent variables in a regression model be at least 104 + *m*, where *m* represents the number of predictors (Tabachnick & Fidell, 2001). The sample size in this study did not meet this requirement regardless of the number of IVs in the model. Others have suggested that it is acceptable to have at least 20 cases per predictors (Meyers et al, 2006). This requirement could have been met with one predictor in the model; however, other important variables would have to be excluded. Thus, the goal was to have as few independent variables as possible in the model yet still maintain any that were significant as well as the group level variable. Due to the small sample size available, the regression models found are not generalizable yet still provide insight into the influence collaboration had on student learning among the participants from this study.

4.3.1 Pre-Analysis Screening

Univariate data screening was previously completed within the two groups – control and treatment – of participants. Though, prior to the regression analysis it was necessary to screen the dependent variables – academic achievement, perceived learning, and statistical knowledge – using the data collected from all participants. The dependent variables were examined for univariate outliers graphically through the use of histograms (see Figure 4.4). The data points were standardized within each dependent variable to

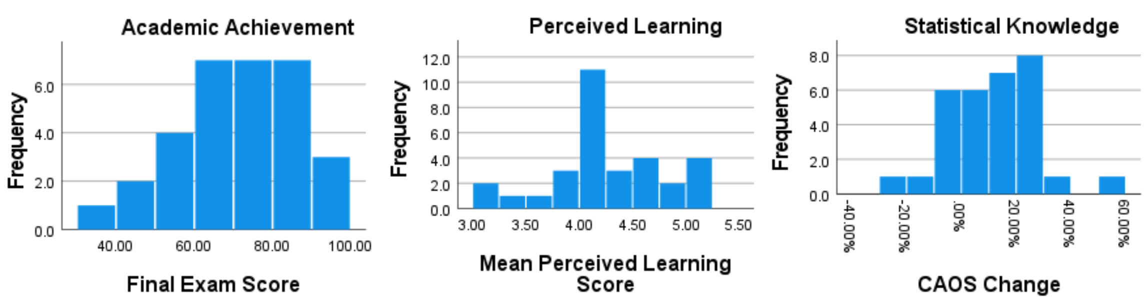


Figure 4.4 Histograms of Dependent Variables

assess whether or not there were any outliers. The most extreme observation was found within the perceived learning variable having a standardized score of z = -2.30 which was within +/- 2.5 standard deviation from the perceived learning mean (Hair et al., 1998).

There also did not appear to be any extreme departures from normality within each of the dependent variables as shown on the histograms (see Figure 4.4).

Additionally, the dependent variables were assessed for normality by calculating the skewness, kurtosis, and Shapiro-Wilk's p-value for each (see Table 4.14). The skewness

Table 4.14 Normality Screening for Dependent Variables

	Skewness	Kurtosis	Shapiro-Wilk (p-value)
Achievement	-0.43	-0.38	.54
Perceived Learning	-0.27	0.05	.16
Statistical Knowledge	0.05	0.42	.55

and kurtosis values all fell within ± 0.5, the most conservative limit for indicating non-normality (Runyon, Coleman, & Pittenger, 2000). All the Shapiro-Wilk's p-values were not significant. Thus, it was assumed that each dependent variable was normally distributed without the presence of any outliers.

Correlations between all variables were obtained to begin examining the relationships between the potential independent variables with the dependent variables. The independent variables considered were participants' age at the start of the course, number of credit hours enrolled during the current semester, cumulative credit hours earned, ACT math and reading scores, cumulative GPA, number of previous online courses, hours worked per week, pre-CAOS score, gender, whether or not the individual was a first-generation college student, whether or not the individual was an underrepresented minority, and number of assignments completed. There were seven assignments possible and were either collaborative or individual based on the section in which the participant was enrolled. The correlations were considered when determining the regression models for each of the dependent variables. One noteworthy correlation that was discovered was a significant negative correlation between pre-CAOS score and whether or not the participant was an underrepresented minority (r = -.519, p = .003).

This suggested a potential bias in the CAOS instrument that has not yet been reported. This finding will be further discussed in the final chapter

4.3.2 Academic Achievement Regression Model

Academic achievement was measured by the participants' score on the final exam. The correlations between academic achievement and all available potential predictor variables were first obtained to begin creating the regression model for academic achieved. Academic achievement had a significant negative correlation with first-generation status (r = -.48, p = .007). This negative correlation was unexpected and led to questioning what can be done to better serve first-generation students in online courses. This will be elaborated upon in the last chapter. There were no other significant correlations. Statistical regression was run to determine what other predictors may be significant (see Table 4.15). Next, the group variable was added to the model to measure its unique influence (see Table 4.16). The final model accounted for 39.9% of the

Table 4.15 Initial Regression Model for Academic Achievement

	B	SE B	β	*t*	*p*
Constant	77.447	3.066		25.259	.000
First Gen	-19.697	4.944	-.670	-3.984	.000
Minority	16.95	6.717	.424	2.523	.018

Note. R^2 = .371

Table 4.16 Final Regression Model for Academic Achievement

	B	SE B	β	*t*	*p*
Constant	79.71	3.67		21.695	.000
First Gen	-20.41	4.97	-.69	-4.111	.000
Minority	16.43	6.71	.41	2.450	.021
Group	-5.18	4.67	.17	-1.109	.277

Note. R^2 = .399

variation in academic achievement, which was only a slight improvement from the R-square of the initial model. The final model shows that when holding all other variables constant, first-generation students scored, on average, 20.41 percentage points lower on the final exam than participants that were not first-generation students; underrepresented minorities scored, on average, 16.43 percentage points higher on the final exam than participants not identified as an underrepresented minority; and participants in the treatment group scored, on average, 5.18 percentage points lower on the final exam than participants in the control group.

After establishing the regression model for academic achievement squared semipartial correlations for each independent variable were calculated. These values provided the unique contribution of each IV toward the variance in academic achievement. The independent variables in the model – first-generation status, underrepresented minority status, and group – had squared semipartial correlations of .375, .134, and .028 respectively. Meaning 37.5% of the variation in academic achievement (final exam scores) was accounted for uniquely by first-generation status, 13.4% of the variation in academic achievement was accounted for uniquely by underrepresented minority status, and 2.8% of the variation in academic achievement was accounted for by the participant’s group. Thus, to address the degree to which collaborative learning contributed to student learning, as measured by academic achievement, it was learned that only 2.8% of the variation in learning in this model was provided by the group level variable independently from all the other predictors variables.

4.3.2.1 Accessing the Academic Achievement Model

The assumptions of normality, homoscedasticity, linearity, and multicollinearity were checked using the final model. Normality of the residuals was examined using a normal predicted probability plot and homoscedasticity was checked with a scatterplot of the predicted values and residuals (see Figure 4.5). The P-P plot showed a fairly linear

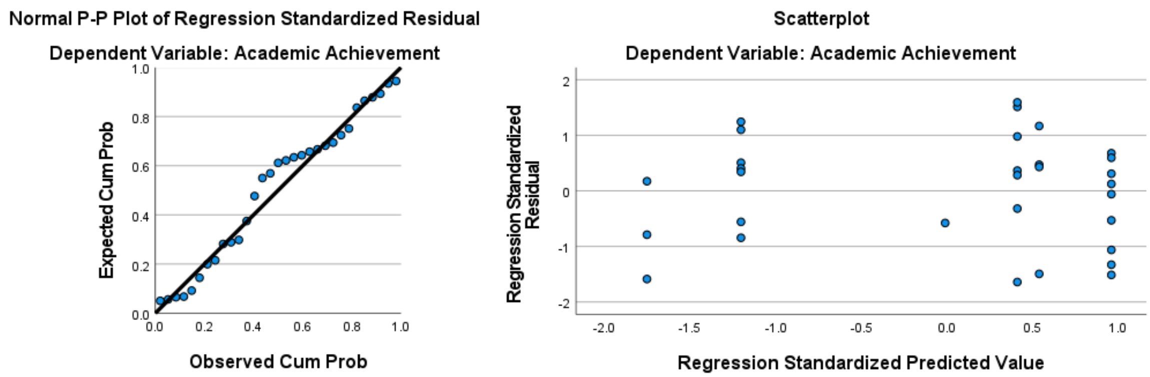


Figure 4.5 Residual Plots for Academic Achievement Model

form signifying normality in the residuals. The scatterplot displayed a fairly even distribution of points around zero on both the X and Y axes suggesting homoscedasticity. The linearity assumption was also satisfied since the residuals were found to be normally distributed and homoscedastic. Finally, multicollinearity was assessed by means of variance inflation factor (VIF) values. The VIF values for first-generation status, underrepresented minority status, and group were 1.28, 1.26, and 1.04 respectively. All of these values were below the most conservative limit of 5, indicating the multicollinearity condition was met as well.

4.3.3 Perceived Learning Regression Model

Perceived learning was measured by participants' mean rating on the perceived learning scale. The perceived learning scale contained eight Likert items each with a one to five rating scale. The correlation coefficients between all the prospective independent variables and perceived learning were calculated and none were found to be significant. The strongest correlation for perceived learning was with the group in which a participant was in (r = -.26, p = .155). When statistical regression for perceived learning was executed no model was fitted. A regression model was then created using the group variable as the single predictor (see table 4.17). The final model shows that participants in

Table 4.17 Final Regression Model for Perceived Learning

	B	SE B	β	*t*	*p*
Constant	4.29	0.11		37.66	<.001
Group	-0.28	0.19	-.26	-1.46	.155

Note. R^2 = .069

the treatment group scored, on average, 0.28 points lower on the perceived learning scale than participants in the control group.

This model accounted for 6.9% of the variation in perceived learning. Further, since group was the only IV used, this is also its unique contribution in the model. Even as the only predictor variable in the model, whether or not a participant experienced collaboration, had little influence on the perceived learning outcome.

4.3.3.1 Accessing the Perceived Learning Model

Assumptions for the perceived learning model were verified in a similar fashion as academic achievement. However, it was not necessary to check multicollinearity since there was only one predictor variable in the model. Figure 4.6 displays the P-P plot and

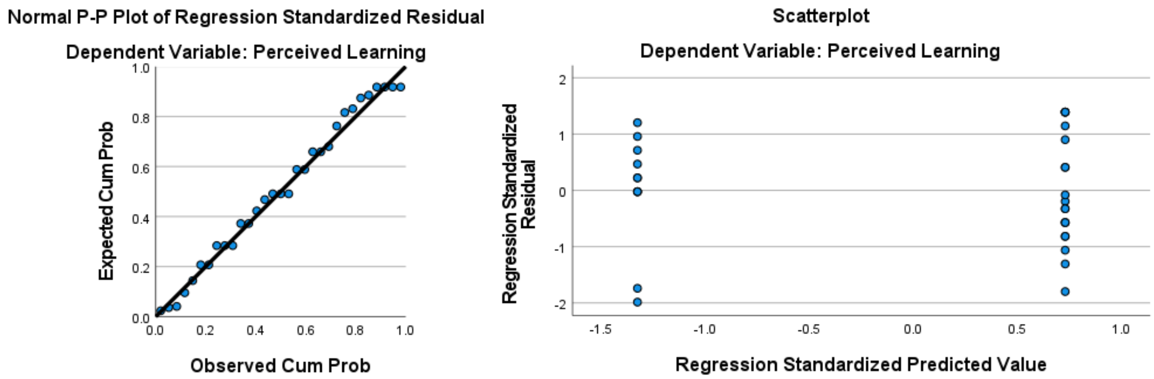


Figure 4.6 Residual Plots for Perceived Learning Model

scatterplot for the residuals in the perceived learning model. The P-P plot had a linear form and the scatterplot had a similar number of points on the left and right of zero on the X axis as well as above and below zero on the Y axis. Therefore, the necessary assumptions of normality, homoscedasticity, and linearity were fulfilled.

4.3.4 Statistical Knowledge Regression Model

Statistical knowledge was quantified by the difference in participants' post-CAOS percentage correct and pre-CAOS percentage correct. A positive statistical knowledge score indicated an increase in a students' CAOS score, and a negative statistical knowledge score indicated a decrease in a students' CAOS score. The correlations between statistical knowledge and all possible predictor variables were computed as a way for considering the most appropriate variables to include in the regression model for statistical knowledge. Statistical knowledge had a significant negative correlation with pre-CAOS percentage correct (r = -.48, p = .007) and a significant positive correlation with number of assignments completed (r = .385, p = .032). The higher an individual's pre-CAOS score the fewer number of items available as *gained knowledge*, so it seemed reasonable for statistical knowledge and pre-CAOS to have a significant negative correlation. The assignments completed for the treatment group were the collaborative assignments; for the treatment group, these were the identical as assignments completed individually. Some of the items on the assignments did require deeper thinking and conceptual understanding, so it is possible that the more of these assignments that were completed – even if done individually – the greater their CAOS gain.

It was assumed that pre-CAOS score and number of assignments completed would be significant predictors in the regression model for statistical knowledge. Statistical regression was implemented to detect the presence of any other significant predictors of statistical knowledge. The initial model (see Table 4.18) found no other significant predictors. After the initial model was observed, the group variable was

Table 4.18 Initial Regression Model for Statistical Knowledge

	B	SE B	β	*t*	*p*
Constant	2.11	17.36		.121	.904
Pre-CAOS	-0.55	0.20	-.43	-2.71	.011
# of assignments	4.71	2.30	.322	2.05	.050

Note. R^2 = .326

Table 4.19 Final Regression Model for Statistical Knowledge

	B	SE B	β	*t*	*p*
Constant	3.24	17.67		0.18	.856
Pre-CAOS	-0.60	0.22	-.47	-2.71	.012
# of assignments	4.66	2.33	.32	2.00	.055
Group	3.36	5.58	.10	0.60	.555

Note. R^2 = .335

included in the model (see Table 4.19). Similar to models used for academic achievement, there was only a slight change in R-square from the initial model to the final model. The final model explained 33.5% of the variation in statistical knowledge. Additionally, the final regression models shows that when the other variables are held constant, for each additional percentage point scored on the pre-CAOS, participants' change in COAS score decreased by 0.6 percentage points, on average; for each additional assignment completed, participants' change in COAS score increased by 4.66 percentage points, on average; and participants in the treatment group change in COAS score was, on average, 3.36 percentage points higher than participants in the control group.

The final regression model was utilized for determining the unique contribution each independent variable had in the variance in statistical knowledge, namely the difference in participants' pre-CAOS score from their post-CAOS score. The squared semipartial correlations for each IV in the model were calculated. The predictors variables in the model – pre-CAOS score, number of assignments completed, and group – had squared semipartial correlations of .181, .099, .009 respectively. Hence, pre-CAOS uniquely contributed to 18.1% of the variance in statistical knowledge, number of assignments completed uniquely contributed to 9.9% of the variation in statistical knowledge, and the group a participant was in uniquely contributed to 0.9% of the variation in statistical knowledge. Again, it was observed here the degree to which collaboration contributed to student learning (as measured by the change in CAOS score) was quite small; 0.9% of the variation in learning in this model was supplied by the group level variable independently from all the other independent variables in the model.

4.3.4.1 Accessing the Statistical Knowledge Model

The final regression model for student learning using statistical knowledge as the dependent variable was verified again as the others before. The appropriate graphs are shown in Figure 4.7. There is an approximate straight-line pattern on the P-P plot and

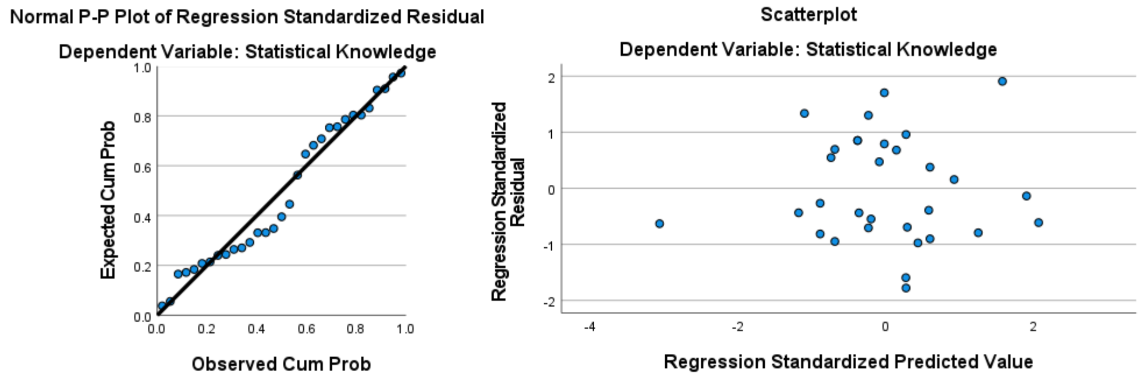


Figure 4.7 Residual Plots for Statistical Knowledge Model

and a sufficient distribution of points on the scatterplot which suggested the conditions of normality, homoscedasticity, and linearity can be assumed. The VIF values for pre-CAOS score, number of assignments completed, and group were reported to be 1.20, 1.02, and 1.18 in that order, which satisfied the multicollinearity assumption.

CHAPTER 5. DISCUSSION, IMPLICATIONS, AND CONCLUSIONS

In this quasi-experimental quantitative study, the influence collaborative learning has on student learning in an asynchronous online introductory statistics course was explored. Participants' learning was evaluated to assess the effectiveness of the collaboration. Few researchers have examined the influence of collaborative learning past academic achievement. Even fewer have described how collaboration affects student learning in online courses and almost none within an asynchronous online introductory statistics course. Differences in learning among all participants that completed assignments collaboratively and participants that worked individually on the same assignments were studied. Similarly, learning outcomes for lower performing students were compared for those that experienced collaboration and those that did not. Additionally, the degree to which collaboration contributed to student learning was quantified.

5.1 Discussion of Results

Unfortunately, no statistically significant results were discovered in this research study. However, there was still plenty of knowledge gained as a result that contributes to the limited body of work in the area of collaborative learning in online education. Each research question will first be addressed followed by a discussion of the overall impact of this study.

5.1.1 First Research Question

To what degree does student learning differ among students that work collaboratively in an asynchronous online introductory statistics course compared with students that work individually in the same setting?

In this study, students that worked collaboratively were not found to have significant differences in learning compared with than those that worked individually. This is similar to the results found by Alqurashi (2019) and (Kapitanoff & Pandey, 2018). However, this is in contrast to the work of many others claiming that collaborative learning improves learning and student performance (e.g. Johnson & Johnson, 2002a, Kurucay & Inan, 2017). The instruments that were selected as a means for measuring student learning – the course final exam, perceived learning scale, and CAOS – have all been shown to have internal consistency, though each were furthered examined to verify whether or not they measured learning as they were intended.

The final exam sought to assess students' knowledge of the course content. There were no significant differences in final exam scores for the two groups. Using exam grades is the most frequent method used for defining student learning (Hiltz & Wellman, 1997). Another instructor that has taught this course at the same institution for numerous years reviewed the final exam implement in this study. It was believed that the final exam contained questions that represented a comprehensive coverage of the course topics. Additionally, of the three instruments implemented in this study, the final exam may be the best indicator of other variables of interest that were not considered here. The grade on the final exam is associated with successful completion of the course which leads to academic persistence and degree completion (Pascarella & Terenzini, 2005).

The perceived learning scale was chosen as a method for quantifying participants' perception of their learning as a result of the course. The participants that worked collaboratively had no significant differences in their perceived learning than those that work collaboratively. However, individuals in the treatment group may have experienced greater learning than what they perceived. Students that experience active learning – such as the collaborative tasks used in this study – have had a lower perception of learning than students that experienced passive learning even when active learning produced higher assessment scores (Deslauriers, McCarty, Miller, Callaghan, & Kestin, 2019). Active and collaborative learning are believed to require more effort than learning that takes place in a more passive environment which is more familiar to students.

The CAOS was selected as a way to evaluate participants' gain in learning. Statistical knowledge gained by the treatment group was not significantly different than the treatment group. When the COAS was originally developed there was a slight, yet significant improvement from students' pretest to posttest scores. On average, at the 95% confidence level, these students scored between 8.2 and 9.9 percentage points higher on the posttest than the pretest (delMas et al., 2007). Though, in order to be included in the sample students had to answer all 40 items and have taken it in class or if not in class, spent at least 10 minutes but less than 60 minutes on completing it. These parameters were not in place for the current study. The scores from all students that agreed to participate were included. Similar results were achieved by the participants in this study. There was a significant – also small – improvement in scores from the pre-CAOS to the post-CAOS ($t(29) = 3.16$, $p = .004$) with a mean post-CAOS score between 3.25 and 15.38 percentage points higher than on the pre-CAOS, using 95% confidence. Therefore, this instrument did assess the degree to which students' gained knowledge as was intended.

5.1.2 Second Research Question

To what degree does student learning differ among lower performing students that work collaboratively in an asynchronous online introductory statistics course compared with lower performing students that work individually in the same setting?

Lower performing students have been found to benefit more from collaborative learning in face-to-face courses, but are less successful in online courses than face-to-face course. For this reason, this study examined the influence of collaborative learning on this particular subset of students. Similar to the findings for all students, lower performing students that completed collaborative assignments did not score significantly different on any of the learning measures than the lower performing students that work individually. It was believed that collaboration would significantly improve learning for lower performing students. This did not occur and is unlike the findings that collaborative learning greatly improves learning for lower performing students in face-to-face courses (Han, et al., 2015; Saner et al., 1994). This finding has not been replicated in an online setting.

5.1.3 Third Research Question

To what degree does collaborative learning contribute to student learning in an asynchronous online introductory statistics course?

This study explored the degree to which collaboration aided student learning through the use of regression models. There are numerous factors that contribute to student learning. Independent variables that were significant predictors of each of the learning measures (dependent variables) were first established. Then the group variable – whether or not the student participated in collaborative tasks – was added to each of the three models. The group variable was not a significant predictor of learning in any of the regression models. After the group variable was included as an independent variable, its unique contribution to the variability in the learning outcomes was minimal.

5.1.4 Overall Impact

By framing this study using social interdependence theory it was predicted that when participants worked together they would outperform those that worked individually. However, this did not happen which lends to asking why not. Perhaps students needed even further guidance on how to interact during collaboration. Learners were expected to work together on the collaborative assignments, but it could not be guaranteed that this took place (Dillenbourg, 1999). Additionally, participants may not have perceived to be learning as much as they actually were when working collaboratively. Effortful learning produces a lower perception of learning than passive learning (Deslauriers et al., 2019). Lastly, it is possible that the collaborative learning that took place in this course was not enough time to make a significant difference on student learning. Participants in the treatment group had the opportunity to work collaboratively for seven hours throughout the course, and they could have chosen not to participate in some of the collaborative session/assignments – or not have been able to due to circumstances out of their control. More time with collaborative groups may be necessary for both creating an environment that in which students are comfortable and improving student learning of the course content.

There have been limited studies examining the influence of collaboration on student learning specifically in the context of an online asynchronous introductory statistics course. Therefore, there is little information available about the types of collaborative learning that best support student learning. One study within an online asynchronous introductory statistics environment compared two different models of collaborative tests and found no significant difference between the consensus versus the non-consensus approaches (Bjornsdottir et al., 2015). Collaborative learning has been shown to have a positive impact on student learning in other environments (Johnson & Johnson 2002a). Further, collaborative learning online can be just as effective or even more effective than collaborative learning in face-to-face courses (Hiltz et al., 2019).

5.2 Implications for Online Statistics Educators

The findings from this study did not support significant improvement in student learning as a result of collaborative learning, though there have been other studies which validate the claim that collaboration expands student learning in online courses (Gunawardena et al., 2010; Kurucay & Inan, 2017). It is worth noting that collaborative learning did not have a significant negative impact on student learning. Therefore, collaborative assignments are still worth incorporating in online statistics courses as there may be other resulting benefits – such as learning to value others' point of view, training students for collaborative settings outside of an educational context, increased sense of belonging, faster progress toward degree completion, higher graduation rates, and an enhance teaching experience (Johnson & Johnson, 1991; Tinto, 1993; Smith &

MacGregor, 1994; Bruffee, 1999; Hiltz et al., 2019), none of which were measured in this study.

Online educators may be hesitant to incorporate collaborative learning in their asynchronous courses, thinking it is not feasible. There are some examples of educators implementing collaborative learning in asynchronous online courses (Robinson, Kilgore, & Warren, 2017), though those are few and far between. Collaborative learning should have face-to-face interaction (Johnson and Johnson, 2002b), but this can be the biggest hurdle in asynchronous learning environments. Giving students control on when meetings take place removes this barrier. This study provides a detailed model in which online statistics educators – or online educators in any field – may use as a starting point for creating a collaborative learning environment in their own courses.

It has recently been reported that many first-generation students struggled with online learning during the pandemic due to other hardships they may have faced, lack of resources, and limited internet access (Soria, Horgos, Chirikov, & Jones-White, 2020). This investigation backed the claim that first-generation students struggle in online courses; academic achievement had a significant negative correlation with first-generation status. First-generation students in this sample scored lower on the final exam, on average, than participants not identified as first-generation students. How online educators – and higher education institutions – can better serve first-generation students in online courses should be considered. What additional supports are needed for improving success rates in this subset of students?

One option available to online educators that supports first-generation students is transparent assessments. It has been suggested that first-generation students are better served when assignments are transparent (Winkelmes, Bernacki, Butler, Zochowski, Golanics, & Weavil, 2016). Assignments that are transparent have a clear purpose, an explanation of how it fits into the class and how it benefits the students, and provide detailed steps for completing and how students will be evaluated. Transparency increases when students are given examples of graded past students' work and tools to evaluate their work. Winkelmes et al. (2016) found that all students benefited from assignments created in the way, but that there was an even greater gain among first-generation students.

5.3 Implications for Future Research

Further investigation that builds upon this research is desirable. First, there is much more to be learn about the participants from this study. It would be advantageous to gather more information about the participants to discover if other benefits were experienced as a result of the collaborative learning in this course. Also, due to the lack of significant results, this study should compel researchers to consider what changes to implement for enhancing student learning. Lastly, this research revealed a weakness in the instrument used for measuring participants statistical knowledge. Opportunities exists for reevaluating and/or updating this instrument.

Collaborative learning has several advantages that were not examined in this work. Any one of these could be isolated for further exploration. As a result of this study, did participants experience any other benefits? Participants could be interviewed for establishing if the collaboration experienced in this course created a lasting sense of belonging or if the collaboration skills developed in the course have been applied in other settings. It would also be valuable to gather future data pertaining to participants' college persistence and graduation rates. Are the participants in the treatment group more likely to remain at the university and graduate than those in the control group? Additional data about participants exposure to other high impact educational practices would be useful. Students that are involved in more than one high impact practice have been described as having even greater gains than those that only experience one high impact practice (Kuh et al., 2017). Can this finding be reproduced using the participants from this study?

This study brought about further questions that build upon the existing research questions. The participants in the collaborative setting in this study had the opportunity for approximately seven hours of collaboration during the semester-long course, though not every student took advantage of all of that time. This then led to speculating that there may be a minimum amount of collaboration required in order to have a significant improvement in student learning. If there is a minimum amount of collaborative time needed, how much is necessary? Further, if the collaboration extends beyond this minimum amount is there an even greater increase in student learning? These questions can be investigated for all students but also for particular subsets of interest. Initially, lower performing students were identified as a potential subset that may experience a greater gain from collaboration. After conducting the study, first-generation students were also identified as a subset that may benefit from more collaboration.

It is also possible that the specifics of the collaborative assignments and/or peer interactions need improvement rather than just needing more time collaborating. What are the unique features of a successful collaborative assignment? The assignments in this study include pre-work, which has been demonstrated to have a significant influence on student learning in other contexts (Koszalka, Pavlov, & Wu, 2021; Cox, 2015). Are there other formats for the assignments that may lead to richer discussions that further develop students' conceptual understanding of introductory statistics? The 21CLD rubric was applied when developing the collaborative tasks. The students were expected to work together, have a shared responsibility, make decisions together, and work interdependently. Students were not evaluated according to this rubric even though the collaborative assignments were designed in this way. Could the 21CLD rubric be used to assess students during their collaborations to ensure students are working together in the intended manner? Or is there a need for a new rubric to be developed for this purpose? The researcher was available for questions during the collaborative meetings but did not remain in the groups' virtual spaces for the entirely of the meetings. It may be worthwhile to record these meetings as a way of evaluating the collaboration.

Lastly, the Comprehensive Assessment of Outcomes in Statistics (CAOS) emerged as having instrument bias. There was a significant moderate negative correlation between participants' pre-CAOS score and their minority status (r = -.519, p = .003). Further, participants identified as an underrepresented minority had a mean pre-COAS score between 6.41 and 27.82 percentage points lower than participants not identified as an underrepresented minority, using a 95% confidence level. This agrees with literature stating instrument bias in many types of standardized tests. In the final iteration of the CAOS development 74% of the students were White (delMas et al., 2007). The CAOS continues to be the primary instrument used for evaluating conceptual understanding of statistics within introductory statistics courses at colleges and universities. There is a need for CAOS scores to be compared between students identified as an underrepresented minority and those that are not by using a larger sample for verifying the claim that the CAOS exhibits instrument bias. If the results from this aspect of the study can be reproduced, the CAOS must be revised or a new instrument measuring college-level introductory statistics knowledge should be created.

5.4 Conclusions

In this study collaborative learning was investigated in the context of an asynchronous online introductory statistics course. It was anticipated that students who took part in collaborative learning assignments would have an enhanced learning experience. The results indicated that there were no significant differences in learning – as measured by academic achievement, perceived learning, and statistical knowledge – between students that worked collaboratively and those that worked individually. Further, there are a plethora of examples stating the benefits of collaborative learning for lower performing students in face-to-face settings (Saner et al. 1994; Webb et al., 1997; Hooper & Hannafin, 1998; Han et al., 2015) but none in online courses. This study did not provide support for the benefit of collaborative learning to lower performing students in online courses. As enrollment in online courses and introductory statistics courses continues to rise (Seaman et al., 2018; Blair et al., 2010), collaborative learning is essential for online course to be as successful as face-to-face courses (Hiltz, 1998). What exactly that collaboration looks like in an asynchronous online introductory statistics course is still to be determined. Given the small sample size available for this study it would be beneficial to gather more data for further exploring the influence collaborative learning has on student learning in an asynchronous online introductory statistics course.

It is hoped that online educators will continue investigating collaboration in their courses with the goal of uncovering the specific aspects of successful collaborative assignments that result in an improvement of student learning.

APPENDICES

APPENDIX A. FINAL EXAM

Final Exam - Requires Respondus LockDown Browser + Webcam

Quiz Instructions

Be sure you have read the Final Exam Information before beginning this exam. This is a cumulative final exam. It covers all the topics from the course. You have two hours to complete this exam. Have a writing utensil, blank loose leaf paper, and a calculator before you begin. You will first complete a series of auto-graded questions (e.g. multiple choice, matching, fill-in-the-blank, etc.). Then you will complete a series of short answer questions. When requested, write your supporting work on your blank loose leaf paper. Organize, label, and clearly write your supporting work. Once you exit the exam you will have 10 minutes to save your handwritten work to the short answer questions and submit as a single PDF file to Final Exam - Supporting Work.

Question 1 2 pts

The slope of a regression equation for a certain data set is 11.0252. Which value could possibly be the correlation for the same data set?

Group of answer choices

11.0252

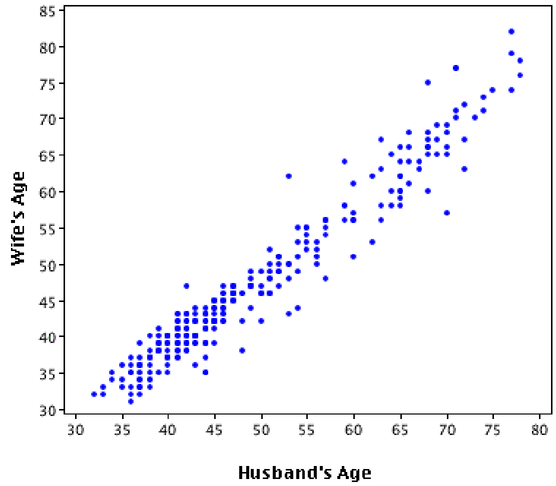
-0.3215

0.7321

2.3871

Question 2 2 pts

What is the value of the linear correlation coefficient for the scatterplot shown below?



Group of answer choices

0.987

1.875

0.582

-0.854

Question 3 2 pts

Which of the following would you expect to have the weakest correlation?

Group of answer choices

Taylor Swift album sales and Taylor Swift concert sales

height and years of work experience

Weight and Body Mass Index (BMI)

hours spent watching T.V. and hours spent studying

Question 4 2 pts

Which of the following statements is true?

Group of answer choices

In order to decrease the likelihood of committing a Type I error choose a smaller significance level.

If the level of confidence decreases, the interval gets wider.

The larger the sample, the larger the margin of error.

Being 95% confident means that 95% of the population was used to calculate the interval.

Question 5 2 pts

A 95% confidence interval to estimate was calculated to be (-12.2312, 8.3424). Which of the following conclusions can be stated about the means of the two samples?

Group of answer choices

More information is need before any conclusions can be made about the means of the two samples.

There is no significance difference in the means of the two samples.

The mean of sample 1 is significantly bigger than the mean of sample 2.

The mean of sample 1 is significantly smaller than the mean of sample 2.

Question 6 2 pts

A hospital wants to determine the effectiveness of a new medication to treat high blood pressure. A study is conducted with a random sample of 90 patients with high blood pressure. In the study, blood pressure lowered for 25 of the patients. Which of the following describes the sample in this scenario?

Group of answer choices

all individuals with high blood pressure

all patients at this hospital with high blood pressure

25 patients whose blood pressure lowered

90 patients with high blood pressure

Question 7 2 pts

Marla would like to see if math aptitude is genetic. She randomly samples 35 students and records his/her math aptitude score as well as the score of one of the student's parents. She will use this data to test for a linear relation between the students' scores and the parents' scores. Which of the following methods would be most appropriate for analyzing these data?

Group of answer choices

two (independent) sample mean

one sample mean

regression analysis

two (dependent) sample mean

Question 8 2 pts

Zinc in drinking water affects the flavor and high concentrations are a health hazard. A scientist wishes to investigate whether the true mean of zinc concentrations in the bottom water of a river exceeds that of the surface water. To do so, sixteen river locations were randomly selected. The zinc concentration was determined for both the surface water and bottom water at each location. Which of the following methods would be most appropriate for analyzing these data?

Group of answer choices

one sample mean

regression analysis

two (independent) sample mean

two (dependent) sample mean

Question 9 2 pts

Do high school students outperform college students in STA 205, on average. A random sample of 300 NKU students that have completed STA 205 is selected. Each student's final grade in STA 205 is recorded as a percentage as well whether they were in high school or not when enrolled in the course. Which of the following methods would be most appropriate for analyzing these data?

Group of answer choices

two (independent) sample mean

chi-square test

regression analysis

two (dependent) sample mean

Question 10 2 pts

A hairstylist would like to estimate the average tip amount she receives from her clients. She records the percentage tip she receives by clients for one month. Which of the following methods would be most appropriate for analyzing these data?

Group of answer choices

two (independent) sample mean

one sample mean

two (dependent) sample mean

one sample proportion

Question 11 2 pts

Census estimates from 2010 state approximately 72% of all US citizens were registered to vote. In the recent presidential election, a push was made to encourage those who were not registered to vote to do so. To see if this has increased voter registration, a random sample of 300 US citizens will be taken. Which of the following methods would be most appropriate for analyzing these data?

Group of answer choices

one sample mean

one sample proportion

chi-square test

regression analysis

Question 12 2 pts

Is the time of day (morning, afternoon, or evening) a class occurs related to the faculty status (part-time or full-time) of the individual assigned to teach the course? A random sample of 250 college classes is planned. The time of day the class takes place and the faculty status of the course instructor is recorded for each class. Which of the following methods would be most appropriate for analyzing these data?

Group of answer choices

chi-square test

regression analysis

one sample mean

one sample proportion

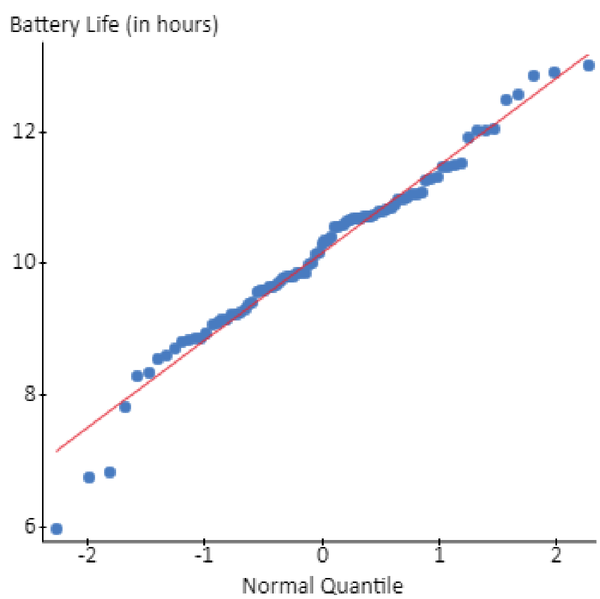
Question 13 4 pts

In a hypothesis test if a Type I error is made this means the sample data ([select] did not support, supported) the alternative hypothesis, but in reality, the alternative hypothesis is ([select] true, false).

Question 14 8 pts

A random sample of 55 iPad Pros was selected and each used under typical conditions. The battery life (in hours) for each is recorded. The sample is summarized in below. Interpret the interval that is two standard deviation from the mean.

([Select] Approximately 95%, At least 90%, Approximately 99.7%, At least 75%) of iPad Pros have a ([Select] battery life, mean battery life) between ([Select] 6.1834, 7.5098, 0) and ([Select] 14.1418, 12.8154) minutes.

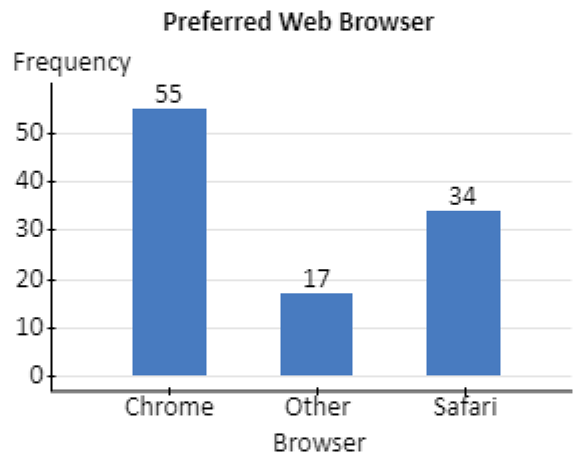


Summary Statistics

Column	**n**	**Mean**	**Variance**	**Std. dev.**	**Median**	**Min**	**Max**	**Q1**	**Q3**
Battery Life (in hours)	85	10.1626	1.7593	1.3264	10.3	5.97	13.01	9.3	10.96

Question 15 6 pts

A recent poll of 106 Americans asked for their preferred web browser. The results are summarized in the graph below.



What was the most popular web browser? [ ]

What percentage of people responded that Safari was their preferred web browser? (Round the percentage to two decimal places.)

[ ]%

We would like to determine if the majority of Americans prefer using Chrome. Which formula should be used to address this? (Type only the letter for the formula selected.)

A. $\hat{p} \pm z\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$

B. $z = \frac{\hat{p}-p}{\sqrt{\frac{p(1-p)}{n}}}$

C. $\bar{y} \pm t(\frac{s}{\sqrt{n}})$

D. $t = \frac{\bar{y}-\mu}{\frac{s}{\sqrt{n}}}$

Question 16 2 pts

A researcher performed the following hypothesis test: H_0: $p = 0.32$ H_A: $p > 0.32$

The test statistic for the test was positive and the p-value was 0.1056. The alternative hypothesis was supposed to be H_A: $p \neq 0.32$. What is the correct p-value for this test? [ ]

Question 17 16 pts

Please type all answers below, labeling each part. Write out supporting work for parts a and b on your loose leaf paper.

A local bar would like to determine if there is a difference for Friday and Saturday in the mean number of drinks sold. A random sample of Fridays and Saturdays is selected and the number of drinks sold each day is recorded.

Difference	**Sample Diff.**	**Std. Error**
Saturday - Friday	354.75371	104.01117

a. Conduct the appropriate hypothesis test using a significance level of 0.05. (7 pts)

possible p-values: 0.0005, 0.0010, 0.9995

b. Estimate the mean difference in the number of drinks sold on Friday and Saturday nights at this bar using 95% confidence. Assume the appropriate critical values is 1.984. (5 pts)

c. Do your results from parts a and b agree with one another? Explain. (4 pts)

Question 18 16 pts

Please type all work and final answers for this question below, labeling each part.

Cincinnati area pools are currently seeking to fill numerous lifeguard position in order to the pool to open this summer. The Cincinnati Recreation Commission (CRC) would like to predict the number of lifeguards employed at each pool based on the number of visitors to the pool. The total number of visitors at the pool in 2021 and the number of lifeguards employed at that location last year are recorded for each of the 23 CRC pool. The corresponding StatCrunch output using this sample is shown below.

Simple linear regression results:

Dependent Variable: # of Lifeguards
Independent Variable: # of visitors
# of Lifeguards = 6.1851897 + 0.001400535 # of visitors
Sample size: 23
R (correlation coefficient) = 0.92105389 (p-value < 0.001)
R-sq = 0.84834027
Estimate of error standard deviation: 0.53512962

Parameter estimates:

Parameter	Estimate	Std. Err.	Alternative	DF	T-Stat	P-value
Intercept	6.1851897	0.69000555	≠ 0	21	8.963971	<0.0001
Slope	0.001400535	0.00012922139	≠ 0	21	10.83826	<0.0001

Predicted values:

X value	Pred. Y	s.e.(Pred. y)	95% C.I.	95% P.I.
5000	13.187865	0.11688799	(12.944783, 13.430946)	(12.048763, 14.326966)

a. Identify the predictor variable and the response variable. (2 pts)

b. Conduct the appropriate hypothesis test to determine if there is a linear relationship between the two variables. Use $\alpha = 0.05$. (6 pts)

c. What is the estimated regression equation? Provide an interpretation of the slope coefficient for this model in context of the variables used. (4 pts)

d. Estimate the average number of lifeguards for pools that have 5000 visitors by interpreting the appropriate interval. (4 pts)

Question 19 13 pts

Please type your final answers (or interpretations) below, labeling each part. Write out the all supporting work for part c on your loose leaf paper.

According to a 2015 report released by the CDC, 9.4% of American adults have diabetes. Researchers would like to know if the proportion of American adults with diabetes has increased. A random sample of 316 US adults is selected. In this sample 30 of the adults were diabetic.

a. What is the population of interest in this scenario? (2 pts)

b. What is the variable being recorded about the individuals? Identify the variable as either categorical or quantitative. (4 pts)

c. Conduct the appropriate hypothesis test using a significance level of 0.05. (7 pts)

Question 20 9 pts

Please type your final answers (or interpretations) below, labeling each part. Write out supporting work on your loose leaf paper.

A company that makes children's glasses would like to investigate whether there is an association between gender and if a child wears glasses. They conduct a survey of guardians of children (under 18 years old). The gender of each child and whether or not they wear classes is recorded. Use the StatCrunch output below to answer the questions that follow.

Contingency table results:
Rows: Gender
Columns: None

Cell format
Count (Expected count) (Contributions to Chi-Square)

	No	Yes	Total
Boy	159 (0.47)	44 (1.35)	203
Girl	180 (0.38)	74 (1.08)	254
Total	339	118	457

Chi-Square test:

Statistic	DF	Value	P-value
Chi-square	1		0.0702

a. Compute the number of boys we would expect to wear glasses if there is no relationship between the two variables. (3 pts)

b. Conduct the appropriate hypothesis test to determine if there is a relationship between gender and if a child wears glasses using a significance level of 0.05. (6 pts)

Question 21 2 pts

I understand that after I submit this exam I will have 10 minutes to save and upload my work for the questions that required supporting work as a single PDF file. I will not access any other web pages or look at any other resources until after I upload my work. I will not speak to any other person about this exam nor share my work with any other student. All work that I am submitting and will submit is my own.

Group of answer choices

no

yes

APPENDIX B. FINAL EXAM FORMULA SHEET

Normal Distributions	$z = \frac{y-\mu}{\sigma}$ $y = z\sigma + \mu$

Sampling Distribution of the Sample Proportion	$\mu_{\hat{p}} = p$ $\sigma_{\hat{p}} = \sqrt{\frac{p(1-p)}{n}}$ np $\geq$ 10 and n(1 – p) $\geq$ 10	$z = \frac{\hat{p}-p}{\sqrt{\frac{p(1-p)}{n}}}$

			Type of Inference	
		Assumptions	**Confidence Interval**	**Hypothesis Test**
ONE SAMPLE	**Proportion**	– random sample of *categorical* data – np $\geq$ 10 and n(1 – p) $\geq$ 10 (for an interval, replace p with $\hat{p}$)	$\hat{p} \pm z\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$ sample size: $n = \left(\frac{z}{\text{MOE}}\right)^2 \hat{p}(1-\hat{p})$	$z = \frac{\hat{p}-p}{\sqrt{\frac{p(1-p)}{n}}}$

Level of Confidence	90%	95%	96%	98%	99%
Critical z value	1.645	1.96	2.054	2.326	2.576

		Assumptions	**Expected Counts**	**Hypothesis Test**
Relationship btwn ≥ 2 categorical variables	**Chi-Square Test**	– random sample(s) of *categorical* data – all expected counts ≥ 5	$\text{exp} = \frac{\text{column total}}{\text{grand total}} * \text{row total}$	$X^2 = \sum_{\text{all cells}} \frac{(\text{obs}-\text{exp})^2}{\text{exp}}$

Sampling Distribution of the Sample Mean		
	$\mu_{\bar{y}} = \mu$ $\sigma_{\bar{y}} = \dfrac{\sigma}{\sqrt{n}}$ variable is normally distributed (or n $\geq$ 30)	$z = \dfrac{\bar{y} - \mu}{\dfrac{\sigma}{\sqrt{n}}}$

		Assumptions	Type of Inference: Confidence Interval	Type of Inference: Hypothesis Test
ONE SAMPLE	Mean	– random sample of *quantitative* data – variable is normally distributed (or n $\geq$ 30)	$\bar{y} \pm t\left(\dfrac{s}{\sqrt{n}}\right),\ df = n-1$	$t = \dfrac{\bar{y} - \mu}{\dfrac{s}{\sqrt{n}}},\ df = n-1$
TWO SAMPLE MEAN	Dependent Samples	– random, dependent sample of *quantitative* data – differences are normally distributed (or n $\geq$ 30)	$\bar{y}_d \pm t\left(\dfrac{s_d}{\sqrt{n}}\right),\ df = n-1$	$t = \dfrac{\bar{y}_d - \mu_d}{\dfrac{s_d}{\sqrt{n}}},\ df = n-1$
TWO SAMPLE MEAN	Independent Samples	– random, independent samples of *quantitative* data – variable is normally distributed for both populations (or $n_1 \geq 30$ AND $n_2 \geq 30$)	$(\bar{y}_1 - \bar{y}_2) \pm t\sqrt{\dfrac{s_1^2}{n_1} + \dfrac{s_2^2}{n_2}}$ (df will be given in output)	$t = \dfrac{(\bar{y}_1 - \bar{y}_2) - (\mu_1 - \mu_2)}{\sqrt{\dfrac{s_1^2}{n_1} + \dfrac{s_2^2}{n_2}}}$ (df will be given in output)

		Assumptions	Line of Best Fit	Hypothesis Test
Relationship btwn 2 quantitative variables	Regression	– The relationship between X and Y appears linear on the scatterplot	$y = mx + b$	TS: r

APPENDIX C. PERCEIVED LEARNING SCALE

Please state your level of agreement to each of the following statements as a result of this course:

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I increased my critical thinking skills.					
I increased my ability to integrate facts.					
I increased my ability to critically analyze issues.					
I am more confident in expressing ideas.					
I learned to value other points of view.					
I learned to interrelate important topics and ideas.					
I increased my understanding of basic statistical concepts.					
I learned factual material.					

APPENDIX D. SAMPLE COLLABORATIVE ASSIGNMENT

STA 205 Pre-work Group Assignment 3 - Confidence Interval for the Proportion & Chi-Square Hypothesis Tests

Directions: Fully attempt all questions/parts by writing your answers and all supporting work on a separate piece of paper. Be sure your work is clearly written and organized, labeling each question number and part. Writing in pencil is recommended so that you are able to make edits when you meet with your group. Some parts of the assignment are intentionally missing. These parts will be provided later and will be completed with your group. Leave space on your paper for these questions. Take photos or scan your work and save it as a **single** PDF file. Post your work on your group's discussion board before your group meeting time. (You must have all questions fully attempted in your first post on the discussion board to receive any credit for the assignment.)

1. In 2021, more than 75% of U.S. colleges and universities did not require the SAT or ACT for admission. Many are promising to continue not requiring the SAT or ACT. In a random sample of 323 U.S. colleges and universities, 194 stated that they will not be requiring the SAT or ACT for admission for the 2022-23 school year.

    a. What variable is recorded for each individual sampled? Classify the variable as categorical or quantitative.

    b. Estimate the proportion of U.S. colleges and universities that will not be requiring the SAT or ACT for admission for the 2022-23 school year with 99% confidence. (Round decimal calculations to four decimal places.)

    c.

    d. If the previous estimate is used and the confidence level remained the same, what size sample should be used to have margin of error within ± 2.5%?

    e.

2. A recent survey of Americans was used to estimate the percentage of Americans with credit card debt. Using this sample, with 95% confidence it is estimated that between 46.17% and 51.78% of Americans have credit card debt. Suppose the following hypothesis test had been conducted using the same sample: H_0: $p = 0.50$ H_A: $p \neq 0.50$, where p represents the proportion of Americans having credit card debt.

    a. Which of the following describes the p-value for this hypothesis test?

        - The p-value would be less than 0.05.
        - The p-value would be more than 0.05.
        - There is not enough information to determine the p-value.

b.

3. A group of middle school teachers are concerned that many of their students are not completing their homework. In hopes of improving the homework completion rate, the teachers develop a homework incentive plan. 80 students are selected and assigned an identical homework assignment. They are randomly assigned to one of two groups – the incentivized group or the control group. Then the teachers will record whether or not each student completed the homework assignment.

   a. What are the **two** variables recorded about the individuals? Identify whether the variables are quantitative or categorical.

   Before the homework assignment is due, the teachers assume there is no difference between the two groups with respect to completing the assignment. Under this assumption, we can identify how many students we expect to complete the assignment in each group. The row totals and column totals are given in the 2x2 *contingency table* below.

   b. Using this information, calculate how many students we would **<u>expect</u>** in each cell when we assume there is no difference between the two groups with respect to completing the assignment.

Group	Number **<u>expected</u>** to complete assignment	Number **<u>expected</u>** to not complete	Total
Incentive			48
Control			32
Total	56	24	80

   This table is what the teachers will use as the benchmark to reason if the results from their experiment seem plausible due to the variability that is expected in samples or if their results are surprising.

   The actual experiment results in the following observations:

Group	Completed assignment	Did not complete	Total
Incentive	40	8	48
Control	16	16	32
Total	56	24	80

c.

d. Find the percentage of students in each group that did and did not complete the assignment.

	Percent that completed	Percent that did not complete
Incentive		

	Percent that completed	Percent that did not complete
Control		

e.

f.

STA 205 Group Assignment 3 - Confidence Interval for the Proportion & Chi-Square Hypothesis Tests

Directions: Discuss your answers to the pre-work with your group. Make corrections on your previous work as needed. With your group, discuss and answer the new questions. Add the work for the new questions on your own paper, writing out all work where appropriate. Take photos or scan your work and save as a **single** PDF file for submission. One student's paper will be randomly selected for grading. The grade earned on that paper will be the grade earned by everyone in the group that participates in the group meeting. Be sure your name is at the top of your paper. There are 10 points possible.

1. In 2021, more than 75% of U.S. colleges and universities did not require the SAT or ACT for admission. Many are promising to continue not requiring the SAT or ACT. In a random sample of 323 U.S. colleges and universities, 194 stated that they will not be requiring the SAT or ACT for admission for the 2022-23 school year.

    a. What variable is recorded for each individual sampled? Classify the variable as categorical or quantitative.

    b. Estimate the proportion of U.S. colleges and universities that will not be requiring the SAT or ACT for admission for the 2022-23 school year with 99% confidence. (Round decimal calculations to four decimal places.)

    c. Does the interval calculated in part b support that claim that more than 60% of U.S. colleges and universities will not be requiring the SAT or ACT for admission for the 2022-23 school? Explain.

    d. If the previous estimate is used and the confidence level remained the same, what size sample should be used to have margin of error within ± 2.5%?

    e. If the previous estimate is **not** used and the confidence level remained the same, what size sample should be used to have margin of error within ± 2.5%?

2. A recent survey of Americans was used to estimate the percentage of Americans with credit card debt. Using this sample, with 95% confidence it is estimated that between 46.17% and 51.78% of Americans have credit card debt. Suppose the following hypothesis test had been conducted using the same sample: H_0: $p = 0.50$ H_A: $p \neq 0.50$, where p represents the proportion of Americans having credit card debt.

    a. Which of the following describes the p-value for this hypothesis test?

        - The p-value would be less than 0.05.
        - The p-value would be more than 0.05.
        - There is not enough information to determine the p-value.

b. Explain your answer to part a. (Hint: Start by considering whether or not Ha is supported by the interval.)

3. A group of middle school teachers are concerned that many of their students are not completing their homework. In hopes of improving the homework completion rate, the teachers develop a homework incentive plan. 80 students are selected and assigned an identical homework assignment. They are randomly assigned to one of two groups – the incentivized group or the control group. Then the teachers will record whether or not each student completed the homework assignment.

   a. What are the **two** variables recorded about the individuals? Identify whether the variables are quantitative or categorical.

   Before the homework assignment is due, the teachers assume there is no difference between the two groups with respect to completing the assignment. Under this assumption, we can identify how many students we expect to complete the assignment in each group. The row totals and column totals are given in the 2x2 *contingency table* below.

   b. Using this information, calculate how many students we would **expect** in each cell when we assume there is no difference between the two groups with respect to completing the assignment.

Group	Number **expected** to complete assignment	Number **expected** to not complete	Total
Incentive			48
Control			32
Total	56	24	80

   This table is what the teachers will use as the benchmark to reason if the results from their experiment seem plausible due to the variability that is expected in samples or if their results are surprising.

   The actual experiment results in the following observations:

Group	Completed assignment	Did not complete	Total
Incentive	40	8	48
Control	16	16	32
Total	56	24	80

c. Based on the results from the experiment do you think there is relationship between the group a student is in (incentive v. control) and whether or not they complete their assignment? Explain.

d. Find the percentage of students in each group that did and did not complete the assignment.

	Percent that completed	Percent that did not complete
Incentive		

	Percent that completed	Percent that did not complete
Control		

e. Based on the percentages in part d, do you think there is relationship between the group a student is in (incentive v. control) and whether or not they complete their assignment? Explain.

f. To determine if the differences in these percentages are *significant*, we need to conduct a hypothesis test. What would our hypotheses be?

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EDUCATION

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TEACHING EXPERIENCE

Northern Kentucky University — 2011 – present
Department of Mathematics & Statistics
Lecturer

ITT Technical Institute — 2010 – 2011
Adjunct Instructor
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Beckfield College — 2010
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University of Cincinnati — 2008 – 2010
Teaching Assistant
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OTHER PROFESSIONAL EXPERIENCE

Kentucky Center for Mathematics — 2015
Faculty Associate

PUBLICATION

Lemmon, M. (2015). *Transdisciplinary preparation of preservice secondary math and science teachers*. In M. J. Mohr-Schroeder & J. Thomas (Eds.), Proceedings of the

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PROFESSIONAL HONORS

Recognized by an NKU graduating senior as having a positive impact on their academic and/or personal development	multiple semesters

Professional Memberships

NKU College of Arts and Sciences Student Success Fellowship Recipient	2021