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Changing attitudes and facilitating understanding in the undergraduate statistics classroom: A collaborative learning approach

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Abstract: Collaborative and problem-based learning strategies are theorized to be effective methods for strengthening undergraduate science, technology, engineering, and mathematics education. Peer-Led Team Learning (PLTL) is a collaborative learning technique that engages students in problem solving and discussion under the guidance of a trained peer facilitator. This comparative study investigates the impact of a PLTL-based learning community program on both content mastery and dispositions of undergraduate students taking an introductory course in applied statistics. Results suggest that students participating in the learning community program acquired significantly greater content mastery in statistics when compared to non-participating peers. Moreover, the learning community experience may provide students with a buffer against developing the negative attitudes and perceptions that often pervade the undergraduate applied statistics classroom.

Keywords: statistics education, collaborative learning, peer-led team learning, student attitudes, learning outcomes

Statistics educators face significant challenges with engaging undergraduate students in applied statistics courses. These students may have insufficient mathematical or statistical preparation for the statistics course that they are required to complete (Johnson & Kuennen, 2006), and it is not uncommon for undergraduate students to adhere to misconceptions about statistical concepts and faulty statistical reasoning (Garfield & Ahlgren, 1988; delMas & Garfield, 1999; Kahneman, Slovic, & Tversky (1982) as cited in Garfield, 1995; Konold, 1995; Hirsch & O'Donnell, 2001; Castro Sotos, Vanhoof, Van den Noortgate, & Onghena, 2009). Accompanying a lack of academic readiness for post-secondary coursework in applied statistics is often some degree of math-related anxiety or phobia, negative attitudes toward the content or discipline, an overall lack of interest in statistics, or the perception that the course is irrelevant to their chosen major (Gal & Ginsburg 1994; Gal, Ginsburg, & Schau, 1997). Ultimately, these attitudes have been found to be correlated with course performance (Finney & Schraw, 2003; Dempster & McCorry, 2009). Unfortunately for statistics educators, attitudes toward the course and course content, in general, have been found to be difficult to change (Garfield & Ahlgren, 1988; Garfield & Ben-Zvi, 2007). These challenges, both academic and attitudinal, may be particularly pronounced for those educators who teach courses for non-statistics or mathematics majors who enrolled in the

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course chiefly to fulfill a general graduation requirement or a specific requirement for their majors.

Given the challenges encountered in introductory statistics courses offered at the undergraduate level, educators have looked for ways to improve statistics education. Research on the use of collaborative learning strategies in undergraduate STEM education, in general, suggests that collaborative learning can be a highly effective means for promoting the kind of understanding, problem solving, and social competency that is expected of 21st century professionals (Roseth, Garfield, & Ben-zvi, 2008; Mastascusa, Snyder, & Hoyt 2011). The Guidelines for Assessment and Instruction in Statistics Education (GAISE, 2005) state that statistics educators, specifically, should foster active learning in the classroom through techniques such as group problem solving, hands-on activities and discussion (GAISE, 2005). The aim of this study is to explore the impact of regular, peer-facilitated collaborative problem solving in small-group settings on the learning and attitudes of students taking an introductory course in applied statistics at a medium-sized, liberal arts university in the Midwest.

I. Review of Literature.

A. Collaborative Learning.

One of the major theoretical foundations of collaborative learning is that of social constructivism and the works of psychologist Vygotsky (Cracolice & Tautmann, 2001; Barkely, Cross, & Majro, 2005). Social constructivism is a student-centered view of learning. In constructivist theories, the student (based on past knowledge, experiences, and context of the learning experience) will assimilate new knowledge and construct their own understanding of the information. Social constructivists argue that an important part of constructing this understanding comes from interactions/dialogue with other learners (Svinicki, 2004). While several variations of collaborative learning have been described, at a broad level collaborative learning can be defined as working together to achieve common learning goals.

Elizabeth Barkley and her colleagues (2005) identified three essential elements of collaborative learning: co-labor, intentional design, and meaningful learning. During collaborative learning, all students in the group must be actively engaged (co-labor) in a structured activity designed to complement the course learning objectives (intentional design). This activity results in an increase in a student's knowledge and understanding of course material (meaningful learning).

In the literature, the terms collaborative and cooperative learning are both used to describe situations where students work together to learn, but important distinctions between the two can be made. Bruffee (1995) defines the goal of collaborative learning as shifting the classroom authority from faculty to students and asserts that the goal of cooperative learning is to hold students accountable for learning together. While subtle differences exist, many researchers use the term cooperative and collaborative learning interchangeably. In the review of the literature presented here, the term collaborative learning is used to refer to studies on both collaborative and cooperative learning.

It is well established that in many disciplines and at different education levels collaborative learning has a positive impact on student achievement and student perceptions of both themselves (improved self esteem) and their relationships with others (social support) (Johnson, Maruyama, Johnson, Nelson, & Skon, 1981; Johnson & Johnson, 1994; Johnson,

Johnson, & Smith, 1998). Specifically in STEM disciplines at the post-secondary level, two large, meta-analyses of research show that collaborative learning has substantial positive impacts on student achievement (Springer, Stanne, & Donovan, 1999; Ruiz-Primo, Briggs, Iverson, Talbot, & Shepard, 2011), attitudes towards material, and self-esteem (Springer et al., 1999).

First, in 1999 Springer and colleagues retrieved 383 collaborative learning reports from undergraduate STEM disciplines published between the years of 1980 and 1999. Of these reports, 39 met the strict inclusion criteria for the analysis. Their results show that collaborative learning positively impacts student achievement (effect size (*d)* = 0.51) and improves student attitudes towards the STEM disciplines (*d* = 0.55). When they examined student attitudes further they found collaborative learning specifically increased self-esteem (*d* = 0.61) and student attitudes towards learning the material (*d* = 0.56). There did not appear to be a relationship between collaborative learning and student motivation to achieve (*d* = 0.18) (Springer et al., 1999). A more recent meta-analysis focused on research in undergraduate STEM disciplines from 1990-2007 supported the results of the Springer study (Ruiz-Primo et al., 2011). It examined the impact of multiple innovative science teaching techniques (including collaborative learning) on student achievement. The authors found that collaborative learning improved student achievement when used alone or in conjunction with other innovated technologies such as the introduction of conceptually oriented tasks (mean *d* ranged from 0.46-0.68). (Ruiz-Primo et al., 2011).

Peer-Led Team Learning. Peer-Led Team Learning (PLTL) is a specific form of collaborative learning initially created by educators to improve student interest and success in chemistry courses (Woodward, Weiner, & Gosser, 1993; Gosser et al., 1996; Gosser & Roth 1998). From its inception in the 1990s, PLTL has gained widespread use in STEM (Science, Technology, Engineering and Mathematics) disciplines. To date, at least twenty-six different colleges and universities have been involved in published PLTL research (Gosser, 2011).

PLTL involves a small group of six to eight students that meet weekly with a peer-leader for approximately two hours to tackle difficult course concepts and problems with their peers. Multiple variations of the PLTL model have been reported. They differ in terms of when the PLTL workshops are held (in or out of class time) and whether participation is voluntary or mandatory for all students (Gafney, 2001). Despite these differences six critical components of PLTL have been identified (Gosser, 2001):

- The PLTL group is an essential component of the course.
- The course professors are involved in the PLTL process both in material design and interactions with the peer leaders.
- Peer-leaders have previously been successful in the course and are selected and trained to be skilled in student learning and group facilitation.
- PLTL group materials are designed for small group work, appropriately challenging and directly related to course material.
- The PLTL group is the correct size and the group is held in a space that encourages small group learning.
- Institutional and departmental support for the approach are available.

The first published report of positive student achievement gains in PLTL came from the Workshop Chemistry Project where an average 15% increase in students receiving A, B, or C grades in PLTL-based courses compared to non-PLTL based courses was reported. (Gafney, 2001). Since this initial account, many research groups have reported significant PLTL derived gains in student achievement in chemistry courses as measured by course grades (Hockings, DeAngelis, & Frey, 2008; Baez-Galib, Colon-Cruz, & Resto, 2005; Lyon & Lagowski, 2008; Quitadamo, Brahler, & Crouch, 2009; Wamser, 2006) and exam scores (Lyon & Lagowski, 2008; Popejoy & Asala, 2013). Additionally, a significant increase in critical thinking skills was reported for students in a PLTL-based general chemistry course compared to their non-PLTL counterparts (Quitadamo et al., 2009).

Consistent with PLTL research in chemistry, significant gains in student learning have also been associated with PLTL in other STEM disciplines including biology (Tenney & Houck, 2003; Petroy-Kelly, 2007; Preszler, 2009), mathematics (Quitadamo et al., 2009; Liou-Mark, Dreyfuss, & Younge, 2010), computer science (Horwitz & Rodger, 2009), and engineering (Loui & Robbins, 2008). In a 2012 review of PLTL research, Gosser reported a 16% average increase in students receiving A, B and C grades in STEM disciplines when exposed to PLTL-based models (Gosser, 2011). Peteroy-Kelly (2007) identified a significant increase in students' conceptual reasoning skills between the beginning and end of the semester in an introductory biology course that incorporated PLTL. While these studies were short-term, focusing on student achievement/learning in the same course where students are exposed to PLTL, a recent study from Penn State-Schuylikk suggests that PLTL benefits might persist beyond the original PLTL-based course. Students who enrolled in a PLTL-modeled one-credit problem solving course accompanying their first semester general chemistry course received higher grades in later chemistry classes than their non-PLTL peers (Eberlein, 2012).

B. Collaborative Learning and PLTL in Applied Statistics.

Like other STEM disciplines, statistics educators have recognized the benefits of collaborative learning for students in their classrooms. Studies have demonstrated greater achievement (as measured by exam scores or total course points earned) in students exposed to collaborative learning techniques compared to their counterparts in introductory statistics courses at both the undergraduate (Keeler & Steinhorst, 1994; Magel, 1998; Ghani, 2009; Perkins & Saris 2001; Giraud, 1997; Potthast 1999; Borreson, 1990) and graduate level (Enders & Diener-West, 2006). In addition to achievement gains, formal and informal assessments suggest that collaborative learning in statistics is viewed positively by most students participating in the experience (Borresen, 1990; Keeler & Steinhorst, 1994).

Published studies on collaborative learning in statistics classrooms focus mostly on in-class collaborative experiences such as small group problem solving (Borresen, 1990; Giraud, 1997; Ghani, 2009) and the jigsaw technique (Perkins & Saris, 2001). These methods differ widely from the PLTL approach described above. In a study most similar to the PLTL method, graduate students in an introductory biostatistics course participated in a one-hour, bi-weekly, project-based learning sessions led by a teaching assistant. In this study, students who participated in learning sessions performed better on course exams than their counterparts (Enders & Diener-West, 2006).

While collaborative learning has been shown to have a positive impact on student attitudes in STEM disciplines (Springer et al., 1999) and is viewed favorably by many statistics students exposed to this form of learning (Borresen, 1990; Perkins & Saris, 2001; Keeler & Steinhorst, 1994), specific studies evaluating the impact of collaborative learning on changes in student attitudes towards statistics are lacking. No published research could be identified that focused primarily on changes in student attitudes with regard to collaborative learning. However, a constructivist learning environment (which includes small group work and other active learning strategies) has been found to result in a significant improvement in student attitudes towards statistics and a significant decrease in perceived difficulty of the statistics course (Tsao, 2006) as measured by the Survey of Attitudes Toward Statistics (Schau, Stevens, Dauphinee, & Del Vecchio, 1995). While this result may suggest that constructivist learning environments which promote collaborative learning may increase positive attitudes in students taking introductory statistics courses, these results are not well supported. Carnell (2008) failed to find a significant difference between student attitudes in a small observational study when comparing a constructivistically-framed introductory statistics class that included a student-designed project and a class where the student-designed project was omitted.

Researchers examining the impacts of collaborative, problem-based learning in undergraduate STEM education have found results that are largely consistent with the theory underpinning the use of such learning strategies. However, the impact of collaborative, problem-based learning on the undergraduate student and their experience have been found to depend heavily on programmatic structure and implementation. Moreover, very little research has been conducted with students participating in undergraduate applied statistics courses. The emphasis of this research is to investigate the impact of a structured, collaborative learning program incorporating peer-led team-learning on both content mastery (as measured by exam scores) and the dispositions (as measured by the Survey of Attitudes Toward Statistics) of undergraduate students taking an introductory course in applied statistics.

II. Program Description.

A. Background.

In the fall of 2010, the STEM Learning Community Program (LCP) was introduced to undergraduate students enrolled in science and mathematics courses at a private, medium sized, liberal arts university in the Midwest. The objectives of the STEM LCP were to improve the depth and breadth of student learning in introductory science and mathematics courses, facilitate positive attitudes toward course content and discipline, strengthen student capacity for collaborative engagement, and increase the retention of students in STEM disciplines.

STEM Learning Communities (LCs) have been offered every semester since the fall of 2010 with financial support from the Dean of Arts and Sciences, as well as individual departments. To date, LCs have been offered to students taking 100- and 200-level courses in biology, chemistry, mathematics, and applied statistics. Each STEM LC is course-specific, but not necessarily instructor-specific, and provides an opportunity for students to work together (with a peer facilitator), weekly, to enhance their conceptual understanding of course material and develop collaborative problem solving skills. These stable groups of twelve or fewer participants are completely voluntary; however, enrolled students are expected to maintain active and consistent attendance. Between 180 and 240 students participate in the STEM LCs each semester at this university.

B. Program Structure.

The support structure of the STEM LC program consists of a LC coordinator, four faculty liaisons, and 16-20 peer facilitators that are responsible for up to two LCs each semester.

The STEM LC coordinator oversees day-to-day operations of the STEM LC program (i.e., payroll, reserving meeting spaces, etc.). Additionally, this individual develops and delivers ongoing peer facilitator training, oversees LC enrollment and participation, coordinates regular meetings with faculty liaisons to share LC progress, strategies, activities and issues that arise, manages peer facilitator and LC evaluations, and communicates with the broader faculty, department chairs and academic administrators about the STEM LC program. The LC coordinator is compensated through a course release each semester for the time and effort that is expended on this program.

In this particular program, there is a designated faculty liaison for each discipline in which STEM LCs are offered. The liaisons meet with their peer facilitators on a weekly basis to review group progress and to seek input and feedback regarding the development of collaborative problem solving LC activities. The bulk of each faculty liaisons' time is spent working with their peer facilitators to develop appropriate collaborative problem solving activities for use in LC sessions. Liaisons also meet with the STEM LC coordinator regularly and communicate about the STEM LC program to students, faculty and administration. Each faculty liaison has received formal training in collaborative learning theory and practice and receives a small stipend for their involvement with this program.

Peer facilitators are typically upper-level students who have successfully completed the course and have developed a strong foundation in course content. Moreover, these students have exhibited strong peer-to-peer communication skills in the classroom and appear able to foster a positive and productive learning atmosphere. These individuals are hand-picked and invited by the faculty liaisons to participate as facilitators in the STEM LC program. Each semester, these students participate in approximately six hours of training on group facilitation techniques and collaborative learning strategies provided by the LC coordinator. Peer facilitators work with faculty liaisons to develop discipline-specific collaborative, problem-solving activities. They guide the problem solving process in the context of the LC, but do not tutor or teach. These individuals spend roughly four hours each week on STEM LC commitments: they meet for up to an hour with their faculty liaison, devote approximately one hour to individual preparation for their LC, and, finally, spend one and one-half to two hours facilitating their LC. LC facilitators are paid an hourly wage, similar to that of research assistant, for their time.

III. Methods.

A. Participants.

The participants in this study were 46 students enrolled in one of three sections of an undergraduate course in applied statistics. This 200-level course provided students with an opportunity to learn about probability and random variables in an applied context as well as the application, analysis, interpretation and presentation of descriptive and inferential statistics. The vast majority of students taking this applied statistics course enrolled to fulfill a requirement for their majors or for graduation. Half (n = 23) of these students participated in one of three optional collaborative learning community experiences offered throughout the semester. The other half (n = 23) were selected to be members of the control or comparison group based primarily upon first exam scores. When several potential matches were identified, attempts were made to match students by course section and sex.

The participating students closely reflected the demographics of the students taking this course in applied statistics at this institution (Table 1). Most participating students identified as Caucasian between the ages of 18 and 25. Twenty-nine (63.04%) participants were male and 17 (36.96%) were female. Prior to taking this course in applied statistics, nearly all indicated having completed at least one college-level mathematics course (n = 43, 93.48%) and four years of high school math (n = 39, 84.78%). Nearly half (n = 21, 45.65%) of the students participating in the study reported a major in business; the other half of students reported majors in arts/humanities (n = 2, 4.35%), education (n = 3, 6.52%), pre-medicine (n = 3, 6.52%), biology (n = 4, 8.70%), psychology (n = 6, 13.04%), and other (n = 7, 15.22%). The vast majority of students participating in this study, both learning community members and non-members, expected to earn grades of A or A- in this course (n = 37, 80.43%).

Table 1. Demographics of study participants.

Characteristic	Learning Community Participants (n = 23)	Matched Pairs, Control Group (n = 23)
Race		
Caucasian	78.26%	100.0%
Minority	21.74%	0.0%
Sex		
Male	65.22%	60.87%
Female	34.78%	39.13%
Percent who completed AP math or stats in high school	39.13%	43.48%
Percent who completed at least one college math course	86.96%	100.0%
Percent who *expected* to earn final grade of A / B / C / D or F as indicated on SATS – 36 pre-assessment	82.61 / 13.04 / 4.35 / 0.0	78.26 / 21.74 / 0.0 / 0.0
Average age	19.78 (s = 1.59)	20.22 (s = 1.59)
Average reported GPA	3.37 (s = .31)	3.19 (s = .39)

B. Procedure.

All of the students participating in this study were members of one of three sections of an undergraduate course in applied statistics offered in the spring of 2011. The course sections ran for 65 minutes and were taught back-to-back on a Monday, Wednesday, Friday schedule by the same professor. All classes were held prior to noon. Each class used the same syllabus and textbook, worked from the same set of course notes, covered the same lecture material, and were given the same assignments and exams.

Learning community participation was an optional and completely voluntary component of the course and was discussed with students, in tandem with the syllabus, throughout the first week of the course. To allow for the assessment of students' attitudinal change throughout the semester, the SATS-36 pre-assessment was administered to all consenting students during a regularly scheduled class period in the first week of the course. The assessment was administered using procedures similar to those typically used to administer course evaluations: the instrument and its purpose were briefly introduced to students, students were read the instructions, and the survey administrator left the room while the instrument was being completed by students.

Learning community registration, handled through an online course management system, took place during week two of the semester. Thirty-six learning community spots were available and thirty-two were taken during registration. Learning community sessions began at the start of week three of the spring 2011 semester and continued for 12 weeks through the week of final exams.

Each applied statistics learning community session was structured to reflect the tenants of collaborative learning, providing students with guided opportunities to solve problems together and investigate and apply course material within a friendly, informal context. Applied statistics LC sessions typically began with an icebreaker chosen by the learning community facilitator to meet the specific needs and interests of the participating students. The icebreaker was followed by a carefully constructed collaborative learning or problem solving activity, designed to engage the students with the material and with each other. The session usually concluded with students working together with the peer facilitator to address any areas of confusion or concern from the previous week's lecture, assigned readings, or assigned problems.

The SATS-36 post assessment was administered during class in the last week of the Spring 2011 semester, prior to the week of final exams, to all consenting students. Again, procedures similar to those used to administer course evaluations to students were used.

C. Academic Outcome Measures.

Learning progress and outcomes were assessed using the four exams that are typically administered as a part of this course. These exams consisted primarily of short answer and "multiple justification" questions. Short answer questions allowed the student to structure their own response to the question provided. Multiple justification questions are structured like traditional multiple choice questions; however, in addition to finding the correct answer amongst the four response options provided, students must provide a reasonable justification, or defense, for their chosen response option. A justification may consist of an explanation of a concept, a graph or other diagram, or the mathematical calculations used to arrive at the answer.

Exams covered approximately one-quarter of the course content and, as such, were administered approximately every four weeks throughout the 15-week semester during regularly scheduled class periods. The first exam was given in week four, just following the first learning community session in week three. (Because the introductory learning community session was offered only one week prior to the first exam, it is unlikely to have impacted exam outcomes in any significant or meaningful way.) All exams were graded in a blind fashion by the instructor of the course; additionally, exams from all three course sections were cross-checked for consistency in grading practices.

D. Attitudinal Outcome Measures.

Attitudinal aspects of the student perspective and experience were measured using the Survey of Attitudes Toward Statistics, commonly referred to as the SATS (Schau et. al., 1995). This inventory contains 36 statements, worded either positively or negatively, to which students respond on a 7-point likert scale (1 = Strongly Disagree, 4 = Neutral, 7 = Strongly Agree). The 36 statements can be grouped according to six highly-reliable attitudinal subscales: affect, cognitive competence, value, difficulty, interest and effort. Cronbach's alpha values, which were calculated for each SATS – 36 subscale at pre- and post-assessment, indicate that the attitudinal constructs were measured with a high degree of internal consistency in this study (Table 2).

Table 2. Survey of Attitudes Towards Statistics – 36.

Subscale	Definition; interpretation	No. of Items	Cronbach's Alpha Pre - Post
Affect	Students' feelings concerning statistics; higher scores indicate more positive feelings about statistics.	6	.834 - .831
Cognitive Competence	Students' attitudes about their intellectual knowledge and skills when applied to statistics; higher scores indicate greater feelings of cognitive competence in statistics.	6	.817 - .867
Value	Students' attitudes about the usefulness, relevance and worth of statistics in personal and professional life; higher scores indicate greater perceptions of the utility, relevance and worth of statistics.	9	.855 - .887
Difficulty	Students' attitudes about the difficulty of statistics as a subject; higher scores indicate lowered perceptions of the difficulty of statistics.	7	.752 - .711
Interest	Students' level of individual interest in statistics; higher scores indicate higher levels of interest in statistics.	4	.829 - .902
Effort	Amount of work the student expends to learn statistics; higher scores indicate greater levels of work intended to learn statistics.	4	.696 - .698

III. Data Analysis and Results.

Learning community participants were matched with non-learning community students based on the score earned on the first exam in this applied statistics course. Additionally, when multiple potential matches were located, efforts were made to match learning community participants (LCP) with non-learning community participants (NonP) by course section and sex. In total, there were 23 LCP and NonP pairs that consented to participate in this study and who completed both the SATS – 36 pre- and post-assessments.

A. Academic Outcomes.

To assess the impact of the learning community, if any, on student learning, paired samples t-tests were used to compare the scores earned on course exams by LCPs and NonPs. The assumptions for paired samples *t*-tests were assessed and satisfactorily met for all comparisons. Due to the high number of significance tests being conducted, a Bonferroni adjustment was applied to alpha for each set of comparisons being made, thereby reducing the chance of a Type I error. Additionally, descriptive statistical analysis was used to examine the trends observed via inferential analysis in greater detail.

For the first set of comparisons, the LCP were compared to NonP on exams I, II, III and IV. Alpha was adjusted relative to the number of pairwise comparisons being made and was set at .0125 for this set of comparisons. Results indicate that, as expected, exam I scores were nearly identical for LCP and NonP students ($t(22) = 1.00$, $p = 0.328$). On exam II, average scores for LCP and NonP were not significantly different ($t(22) = -0.727$, $p = 0.475$). However, LCPs earned significantly higher scores on exam III than their NonP counterparts ($t(22) = -3.12$, $p = 0.005$). On the final exam, which is non-cumulative, LCPs again scored significantly higher than the matched pairs control group ($t(22) = -3.30$, $p = 0.003$) (Table 3).

Table 3. LCP and NonPs exam score results.

	LCP Mean (sd)	NonP Mean (sd)
Exam I	38.33 (4.48)	38.43 (4.27)
Exam II	36.15 (5.11)	35.20 (4.65)
Exam III**	36.22 (5.66)	31.67 (6.21)
Exam IV**	52.32 (5.45)	48.15 (6.81)

** Statistically significant result at $p \leq .01$

In order to examine these patterns more closely, pairs of participants in this study were broken down into groups based upon the letter grade earned on exam I (Figure 1). On exam I, there were two pairs that earned a grade of D/F, five pairs that earned a grade of C, ten pairs that earned a grade of B, and six pairs that earned a grade of A. It is for those students who earned a grade of C or D/F on exam I that the learning community appeared to have the greatest impact on learning outcomes. The average exam score for LCPs who earned a C or D/F on exam I did not fall below 72.6% for the remainder of the semester; on the other hand, the average score for NonPs who earned a grade of C or D/F on exam I fell as low as 53.8%.

B. Attitudinal Outcomes.

Student attitudes toward statistics were assessed using the SATS – 36 pre-assessment in week 1 of the semester and in week 15 using the SATS – 36 post-assessment. The pre- and post-assessment responses of the LCPs and NonPs were compared using paired samples *t*-tests. Additionally, changes in attitudes over the course of the semester were examined by comparing pre- to post-assessment responses for each group (LCPs and NonPs) using paired samples t-tests. Due to the number of significance tests being conducted, a Bonferroni adjustment was applied to the overall alpha for each set of comparisons. Finally, one global attitudinal item on the SATS - 36, "I will like/like statistics" was examined from pre-assessment to post-assessment for LCPs and NonPs separately using Pearson's correlation (r).

SATS – 36, Pre-Assessment Comparison. LCPs and NonPs were compared on the six attitudinal subscales of the SATS – 36: affect, cognitive competence, value, difficulty, interest, and effort. It was anticipated that the groups would be relatively similar in respect to their course-related dispositions at the start of the course and this was largely demonstrated through the data analysis, using an adjusted alpha = .0083. There were no statistically significant differences between LCPs and NonPs on the aforementioned subscales at the beginning of the course. However, the NonPs average rating on difficulty indicated that they expected the course to be slightly but significantly less difficult than LCPs ($t(22) = 3.482$, $p = .002$) (Table 4).

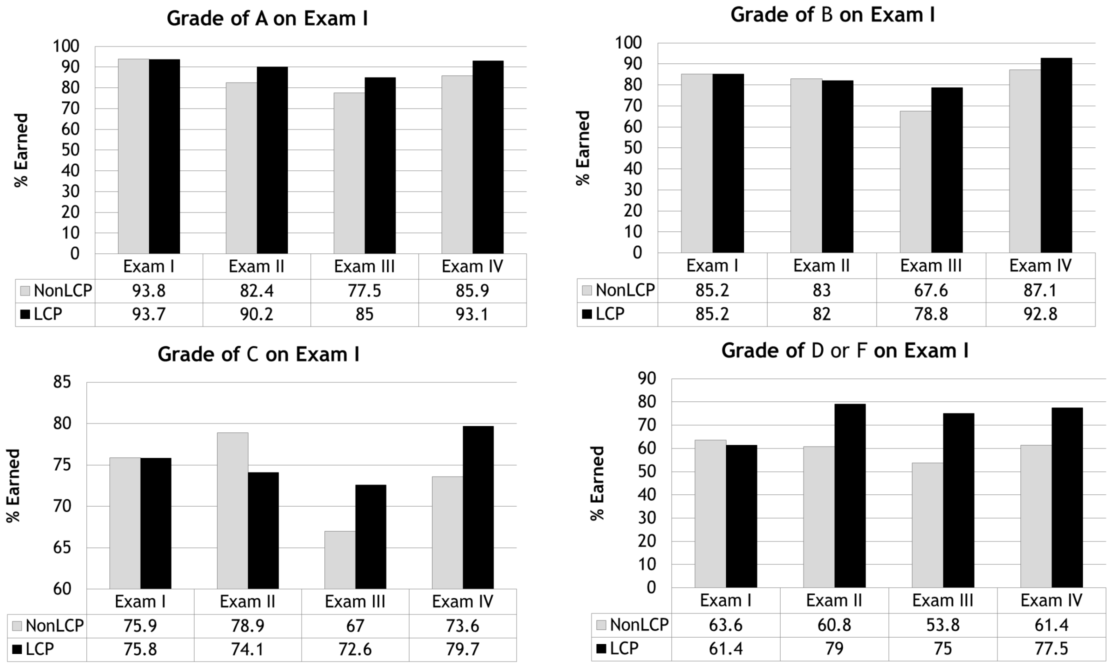

Figure I. Descriptive learning outcomes for LCP and NonPs by grade earned (A, B, C or D/F) on exam I.

Table 4. LCP and NonP means and standard deviations, SATS – 36 pre-assessment.

	LCP Mean (*s*)	NonP Mean (*s*)
Affect	4.30 (0.92)	4.92 (1.05)
Cognitive Competence	5.07 (0.98)	5.49 (0.87)
Value	5.19 (0.80)	5.32 (0.75)
Difficulty**	3.32 (0.40)	3.74 (0.53)
Interest	4.75 (0.88)	4.75 (0.87)
Effort	6.29 (0.61)	6.01 (0.81)

** Statistically significant result at $p \leq .01$

SATS – 36, Post-Assessment Comparison. In order to assess whether there were any statistically significant differences between the LCPs and NonPs on their attitudes toward statistics at the end of the course, these groups were compared on the subscales of the SATS – 36 post-assessment. An adjusted alpha of .0083 was again used as the threshold for statistical significance. Paired-samples t-tests indicate that there were no statistically significant differences between the LCPs and NonPs at the conclusion of the semester in terms of affect, cognitive competence, value, difficulty, interest or effort (Table 5).

Table 5. LCP and NonP means and standard deviations, SATS – 36 post-assessment.

	LCP Mean (*s*)	NonP Mean (*s*)
Affect	4.14 (1.34)	3.73 (1.19)
Cognitive Competence	4.94 (1.20)	4.79 (1.30)
Value	4.73 (0.86)	4.84 (0.97)
Difficulty	3.97 (0.82)	3.80 (0.68)
Interest	3.83 (1.37)	3.93 (1.27)
Effort	5.37 (1.30)	5.29 (1.19)

SATS – 36, Pre- to Post-Assessment, NonPs. Changes in attitude over the course of the semester for NonPs were assessed using paired samples t-tests. An adjusted alpha of .0083 was used as the threshold for detecting statistically significant differences. Average scores on several of the SATS – 36 subscales for NonPs changed from pre-assessment to post-assessment. NonPs were found to have a less positive affect toward statistics at the end of the semester ($t(22) = 6.881$, $p < .001$), to feel less cognitively competent in regard to statistical material and applications ($t(22) = 3.418$, $p = .002$), to express less interested in the subject of statistics ($t(22) = 3.560$, $p = .002$), and to have given less effort than originally intended in the context of the course ($t(22) = 3.418$, $p = .002$). The overall value placed on statistics and perception of the level of difficulty was relatively unchanged for NonPs (Table 6).

Table 6. NonP means and standard deviations, SATS – 36 pre- and post-assessment.

	NonP Pre-Assessment Mean (*s*)	NonP Post-Assessment Mean (s)
Affect***	4.92 (1.05)	3.73 (1.19)
Cognitive Competence**	5.49 (0.87)	4.79 (1.30)
Value	5.32 (0.75)	4.84 (0.97)
Difficulty	3.74 (0.53)	3.80 (0.68)
Interest**	4.75 (0.87)	3.93 (1.27)
Effort**	6.01 (0.81)	5.29 (1.19)

** Statistically significant result, $p \leq .01$
*** Statistically significant result at $p \leq .001$

NonPs attitudes towards statistics at the beginning of the semester, as measured by a global indicator of attitudes toward statistics, were significantly and positively correlated with attitudes toward statistics at the end of the semester ($r = .642$, $p = .001$; $r^2 = .412$). NonP students who anticipated liking statistics at the start of the semester tended to express more favorable attitudes toward statistics at the end. Likewise, NonP students who did not anticipate liking the subject matter at the start of the semester typically held more negative views about statistics at the end of the semester.

SATS-36 Pre- to Post-Assessment, LCPs. The LCPs were also evaluated for changes in attitude over time using the SATs – 36 pre- and post-assessments. The affect LCPs demonstrated toward statistics remained stable over the course of the semester ($p = .543$). Similarly, the LCPs cognitive competence did not change significantly ($p = .517$), nor did LCPs' perceptions of the value of statistics ($p = .024$). Perhaps surprisingly, LCPs found statistics material to be significantly less difficult at the conclusion of the semester ($t(22)$ = -3.958, p = .001) than anticipated at the beginning of the semester. Interest ($t(22)$ = 3.118, p = .005), and actual effort ($t(22)$ = 3.981, p = .001), were reported at significantly lower levels, however, at the end of the semester than at the beginning (Table 7).

Table 7. LCP means and standard deviations, SATS – 36 pre- and post-assessment.

	LCP Pre-Assessment Mean (s)	LCP Post-Assessment Mean (s)
Affect	4.30 (0.92)	4.15 (1.34)
Cognitive Competence	5.07 (0.98)	4.94 (1.20)
Value	5.19 (0.80)	4.73 (0.86)
Difficulty***	3.32 (0.40)	3.97 (0.82)
Interest**	4.75 (0.88)	3.83 (1.37)
Effort***	6.29 (0.61)	5.34 (1.30)

** Statistically significant result at $p \leq .01$
*** Statistically significant result at $p \leq .001$

Unlike the moderately strong correlation found between pre- and post-attitudes towards statistics for NonPs, virtually no correlation was identified for LCPs (r = .040, p = .856; $r^2 = .002$). LCPs who anticipated liking statistics at the start of the semester did not systematically express more favorable or more negative attitudes toward statistics at the conclusion of the semester. Similarly, LCPs who did not anticipate liking the subject matter at the start of the semester did not predictably maintain or change those negative views at the end of the semester.

IV. Discussion.

A. Learning Outcomes.

Inferential Analysis. Inferential analyses indicate that students who participated in the applied statistics LCs performed no differently than their matched pairs on exam II, but significantly better on exams III and IV. Exam II was administered to students just one month after the initiation of the LC. While LC participants certainly had additional structured opportunities to work with the material beyond what was available to NonPs in the month leading up to exam II, it did not result in higher exam scores on exam II for LCPs. This result seems to indicate that a few additional opportunities for collaborative investigation and problem solving are not enough to enhance learning outcomes for undergraduate students taking introductory courses in applied statistics; instead, a longer-term experience with peer-facilitated collaborative learning may be necessary to enhance learning objectives.

Exams III and IV were administered two and three months following initiation of the LC experience and LCPs did in fact earn significantly higher grades than NonPs. Such a result indicates that a LC program may improve the depth and breadth of student learning in the context of an undergraduate course in applied statistics. The fact that exam results of LC participants showed significantly better performance than their matched pairs, but only after an extended period of time working together in stable groups, suggests that the social, collaborative, and ultimately the community-related aspects of the LC experience are important contributors to learning outcomes.

The gradual improvement of student performance throughout the semester has been noted in other PLTL/PLTL-like research (Hockings et al., 2008, Lewis & Lewis, 2005; Peteroy-Kelly, 2007). Like the students in the applied statistics class, students in these studies having been involved in a PLTL experience showed improvement on achievement measures from the beginning to end of the course. Lewis & Lewis (2005) attributed this result to the students' adjustment to the learning method, but these results are also consistent with research on the nature of team development and learning. Varma-Nelson & Coppola (2005) describe the PLTL model of team learning as groups of undergraduates being transformed into a high performing team by another trained undergraduate student. In this model the peer leader plays a significant role in impacting how quickly this transformation takes place (Varma-Nelson & Coppola, 2005). Based on this idea of team learning, it may take time for a team to develop and mature before the positive impact of PLTL on student learning may be seen.

Descriptive Analysis. An examination of the learning outcomes for LCPs and NonPs who earned grades of A, B, C and D/F on exam I lends further insight into the impact of the LC experience. While inferential analysis on the exam results broken down by grade was not conducted in this study due to the small group sizes, descriptive analysis was used to understand the effect of the LC experience on learning outcomes for students earning C or D/F on exam I. Exam I might be considered largely a review exam in that it covers material and concepts with which students should already be familiar prior to enrolling in a college-level course in applied statistics (e.g., measures of center, measures of spread, and graphical and tabular representations of data). Students who perform poorly on such an exam might be identified by the course instructor as at risk for poor performance throughout, and possible failure of, the course. Not incidentally, it is precisely this group of students who need additional concern and investment from the post-secondary instructor of applied statistics.

The LCPs who earned a grade of C or D/F on exam I passed with an average of 72.6% or better on all of their subsequent exams in this course; exam averages for NonPs, more than half the time, fell below 70.0%. Moreover, the LCPs who earned grades of C, or D/F on exam I outperformed their matched pairs counterparts by particularly wide margins on exams III and IV which, in this particular course, include what is generally perceived by students to be most difficult aspects of the course (e.g., the central limit theorem, sampling distributions, and applications of hypothesis testing in a wide array of contexts). For the students participating in this study, the LC experience was of particular benefit to those who might have been identified as at-risk based on exam I performance. This result suggests that further empirical research on the benefits of collaborative learning, and PLTL in particular, for lower-achieving or at-risk students in post-secondary applied statistics is warranted.

B. Attitudinal Outcomes.

Student attitudes are an important consideration in introductory statistics courses. Attitudes can impact student learning and a student's ability/motivation to apply statistics outside of the course context (Gal et al., 1997) and should be viewed as an important course outcome (Schau & Emmioglu, 2012). Emmioglu & Capa-Aydin (2012) conducted a meta-analysis to examine the relationship between attitudes and statistics achievement in undergraduate classrooms around the world. Focusing on studies that used the SATS-28, they identified 17 studies (published between

1998 and 2011) that met their inclusion criteria. Collectively they report that affect (r = 0.30), cognitive competence (r = 0.30), value (r = 0.21) and difficulty (r = 0.20) are all moderately and significantly correlated with course achievement.

Pre-Assessment. At the start of the semester, the LCPs and NonPs were very similar in terms of their pre-conceived attitudes toward statistics as measured by the six subscales of the SATS – 36. The averages for both groups were similarly high on the subscales of cognitive competence, value and effort during the first week of the course. Such results indicate that LCPs and NonPs alike felt that applied statistics is a relevant and useful discipline worthy of investigation, they felt well prepared to master the material, and they held high expectations for their study and work habits. In fact, a preponderance of LCPs and NonPs expected to earn grades of A or A- (82.61% and 78.26%, respectively) as a result of their efforts in the course. However, the exams scores and final grades that followed were not consistent with such a high degree of initial perceived cognitive competence, anticipated effort and follow-through, or their expected grade outcome.

The initial attitudes towards statistics held by both the LCPs and NonPs in the applied statistics course are consistent with results of past studies (Evans, 2007; Schau & Emmioglu, 2012). One particular study conducted by Schau and Emmioglu (2012) examined the attitudes of 2200 students enrolled in post-secondary introductory statistics courses at multiple institutions in the United States using the SATS - 36. On average, at the start of the semester the students in this large study felt the discipline and study of statistics was relevant ($\bar{x}_{Value}$ = 5.05, n = 2,186), they were confident in their abilities to master the subject ($\bar{x}_{Cognitive\ Competence}$ = 4.94, n = 2,192) and expected to put in a large amount of effort ($\bar{x}_{Effort}$ = 6.32, n = 2,246). Consistent with the results of this study, students enter statistics courses confident they will perform well; however, confidence is not generally indicative of performance in the introductory statistics course. This inconsistency may suggest of a widespread misconception about the contents and expectations of an introductory course in applied statistics at the post-secondary level.

Attitudes between LCPs and NonPs were similarly neutral on the subscales of affect and interest. Students expressed neither overtly positive nor negative attitudes toward personal interest in the discipline of applied statistics. Given that none of these students were mathematics or statistics majors and all were taking this class solely as a requirement for their majors or for graduation, such neutral attitudes are not surprising.

Only in terms of the expected difficulty of the course were the LCPs and NonPs found to differ at the time of pre-assessment. As indicated by their means, both groups perceived the field of applied statistics to be relatively difficult (as opposed to relatively easy). On average, however, the LCPs expected the course to be slightly, but significantly, more difficult than the NonPs. This finding might be expected as those who perceive the course to be more difficult at its outset would be more likely to enroll in a voluntary program such as the one offered.

Post-Assessment. At the conclusion of the semester, responses to the SATS - 36 post-assessment indicate that there were no statistically significant differences between LCPs and NonPs on the six attitudinal subscales of affect, cognitive competence, value, difficulty, interest and effort. The only subscale that maintained its positive average was effort, whereby both LCPs and NonPs agreed that they put forth a high degree of effort throughout the course. At post assessment, relatively neutral attitudes were expressed by LCPs and NonPs on the subscales of affect, cognitive competence, and value. Finally, LCPs and NonPs alike found the study of applied statistics to be relatively difficult and expressed a rather low degree of personal interest in the discipline at the conclusion of the semester. Perhaps not surprisingly, neither of the student groups who participated in this study came away from the course with overwhelmingly positive attitudes toward the course content or discipline of applied statistics. It would appear that the Learning Community Program does not effectively improve the attitudes of undergraduate students taking an introductory course in applied statistics to fulfill a program or graduation requirement; this is further evidence to support the assertion that attitudes toward statistics are exceptionally difficult to change in the context of a course (Evans, 2007; Sizemore & Lewandowski, 2009; Schau & Emmioglu, 2012).

Change Over Time. However, an examination of attitudes at the conclusion of the course only tells a portion of the story. To more thoroughly investigate the impact of the LC program on participants relative to non-participants, changes in the attitudinal subscales were examined over the course of the semester. The results of inferential analysis indicate that NonPs experienced a significant decline in their attitudes. Significant changes were found for NonPs over the course of the semester on four of the six SATS-36 subscales: affect, cognitive competence, interest and effort. More specifically, NonPs reported feeling less positive toward the discipline, less competent with the material, less interested in the discipline and material, and expending less effort at the end of the semester than what was anticipated at the beginning. The fact that the attitudes toward the course and discipline by NonPs at the end of the semester were consistently more negative at the end of the semester than at the beginning is troubling in that negative attitudes only hinder a student's ability to learn and appropriately generalize the material to relevant contexts. Only the NonPs' expressions of the utility and relevance (value) of the course/discipline and difficulty of the material remained unchanged from the beginning to the end of the semester.

The pre-to post assessment results for LCPs were different from those of NonPs in several areas. While LCPs also expressed significant decreases in interest and effort at the conclusion of the semester, perceived cognitive competence remained stable from the beginning to the end of the semester for LCPs. In other words, the LCPs were able to maintain their relatively strong feelings of cognitive competence in the context of applied statistics. Such a result may have been bolstered by the fact that LCPs, in general, tended to perform better than their matched-pairs counterparts on the exams throughout the semester. Furthermore, the attitude of LCPs towards statistics (e.g., the affect subscale) was stable from pre- to post-assessment. This means that the level of positivity for statistics expressed by LCPs at the beginning of the semester was unchanged at the end of the semester. The difference in results for LCPs and NonPs on perceived cognitive competence and affect may signify the presence of a buffering effect whereby the LC experience, due to the provision of a stable, safe and supportive atmosphere to explore course content and applications, protects participants from a significant decrease in perceived statistics-related competence and affinity. This result is important in that students who do not feel overly negative towards the course or discipline have one less barrier to learning the material, achieving success in the course, and applying course material outside of the context of the course. Moreover, students who feel that they are capable of mastering the material are likely to try to accomplish that goal (Gal et al., 1997).

The final area of contrast for LCPs and NonPs was in terms of perceived difficulty of the course and discipline. While NonPs did not change their perception of the course and discipline from pre- to post-assessment, LCPs reported a lower degree of perceived difficulty at the end of the course than at the beginning. In other words, LCPs' experience in the course helped them to find the material (and its applications) to be more manageable and easily mastered than anticipated. This result can be linked directly to one of the primary objectives of the STEM

Learning Community Program: to strengthen the capacity for collaborative engagement and problem solving. The perception that course content was less difficult than anticipated is likely due to the LCPs enhanced capacity to solve statistics-related problems and apply course content to unfamiliar contexts. In respect to perceived difficulty of the subject, the impact of the LC may extend beyond a buffering effect to actually promoting the kinds of attitudes that foster achievement in post-secondary education.

The importance of buffers on student attitudes and outcomes has been reviewed by Gal and Ginsburg (1994). They suggest that statistics students may experience a series of events similar to the one that math students encounter when course material is difficult and understanding of the material is challenged. When a failure to understand course material takes place, it is usually followed by a failure to receive adequate explanations from the instructor or even peers trying to help. This leads to decreased confidence and panic over a perceived lack of control in the learning process. The student may become bored and disengage entirely. Further, when also considering the negative views of both the course and its content, the student may experience a lifetime of frustration towards the discipline. Programs that foster opportunities for collaborative learning, however, may offer a buffer from these frustrations thus decreasing the likelihood of having an overall negative experience. This could be attributed from support of others encountering similar experiences, thus increasing individuals' confidence and eventually promoting success and achievement.

In addition to the possible buffer that these learning communities may offer, it could also be suggested that they may increase motivation of the enrolled students as well. Bude et al. (2007) built a model of motivation specifically for statistics based on the motivational theories of learned helplessness and attribution. They suggest that educators need to build a learning environment that allows students to tackle feasible tasks. By doing so, students may experience the feeling of success through mastering a certain task. They may then feel more compelled to study and their motivation is heightened because the task/subject at hand now seems attainable. It is believed that these learning communities may offer students the platform on which to accomplish tasks assigned in lecture in a safe and supportive environment outside of the classroom. As a result, the students are able to build a foundation for their studies, solve problems and get feedback from others about the process. This may increase a student's accountability to the group as well as to themselves. Additionally, their self worth and motivation to study increases and leads to improved performance in the course.

Global Assessment – Attitudinal Item. As noted, LCPs and NonPs differed in terms of the change in their overall attitudes toward statistics over the course of the semester. For NonPs, their attitudes toward statistics became significantly more negative as a result of their experience in the class. For LCPs, there was no change in attitude over the course of the semester. Results of correlational analysis on a single global attitudinal item, "I like/will like statistics", yield insight into these pre- and post-assessment attitudes for LCPs and NonPs. As might be expected, attitudes toward statistics as measured by the global attitudinal item at the time of pre-assessment were strongly and positively correlated with the attitudes as measured at the time of post-assessment for NonPs. More specifically, there was a tendency for NonPs who came into the course with relatively favorable responses to the question to leave the course the same way; NonPs who entered the course with relatively negative responses to the question were likely to complete the semester holding on to their negative views. The attitudes of NonPs toward statistics, no matter how accurate or misconceived, were not impacted through regular course participation.

LCPs had very different results on the global attitudinal item, however. The attitudes toward statistics held by LCPs at the beginning of the semester, as measured by the global attitudinal item, were completely uncorrelated to their responses on this item at the semester's end. In other words, there was no systematic tendency for LCPs to leave the course with similar (or opposite) attitudes to what they entered with. For better or for worse, LCPs' attitudes toward the study and discipline of applied statistics were changed, but on an individual basis; the change that one LCP experienced was not necessarily indicative of the chance that another LCP experienced. This statistical result may provide evidence for the potential for a learning community program, like the one investigated here, to provide students with the level of engagement necessary for a highly personalized and meaningful educational experience in the context of an undergraduate course in applied statistics.

V. Conclusion.

Statistics educators face substantial hurdles to engaging their undergraduate non-majors. Whether these students lack the appropriate academic preparation, hold conceptual misconceptions about the material, or simply possess a general lack of interest in the subject, academic and attitudinal barriers can negatively impact students' experiences, attitudes, and course outcomes. As is evidenced by the accumulating research on engaging the hearts and minds of undergraduate statistics students, this is a topic of concern for many. Because it is important that students learn the content offered in an applied statistics course to further the depth and breadth of understanding in their chosen majors, statistics educators must continually strive for ways to stimulate and engage their intellects, while enhancing the accessibility of the material. As demonstrated in this study, the depth and breadth of learning by students in an introductory statistics classroom can be significantly and meaningfully enhanced through a structured peer-led collaborative learning program. While further research is necessary to establish the generalizability of this outcome, peer-led collaborative learning was particularly impactful for the students in this study who were most at risk for failing to meet course learning objectives.

Because student attitudes have been found to be correlated with course performance, statistics educators must also be concerned about the attitudes with which students enter the classroom, the expected trajectory of these attitudes, and how to ultimately minimize the impact of negative attitudes. In general, the students in this study entered the undergraduate statistics classroom with positive attitudes toward the course and discipline and very high expectations for their own competence and performance. However, when the students discovered that the discipline of applied statistics and real-world problem solving is much more complex than calculating batting averages and opinion poll results, many developed feelings of apathy, frustration and discouragement. This trajectory is illuminated by examination of the pre- to post-assessment results of NonPs. LCPs, by contrast, thought that course content actually became *less* difficult over the course of the semester and their sense of cognitive competence remained constant. Moreover, it appears as if the LCPs were able to engage with the class and course material on a very personal and individual level. Unlike the NonPs, the LCPs did not leave this class holding the same attitudes with which they entered and their attitudes did not change in any systematic or predictable way. Such a result may be evocative of a relationship between collaborative learning and change that is possibly transformative in nature; further research is warranted to explore this potential.

Although this study did not employ randomization or utilize strict experimental controls, and the study was implemented throughout just one semester at a singular institution, preliminary results are promising. Frequent, regularly scheduled encounters of guided, collaborative inquiry appear to be an effective strategy for improving learning outcomes for undergraduate students in applied statistics classrooms. Additionally, structured, peer-facilitated collaborative learning may help students cope with the demands of a class for which they have little context and help them to develop an effective buffer against the development of attitudes that can obstruct learning and negatively impact the classroom experience for students and teachers alike.

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