WHAT'S IN A TEAM? PEER EFFECTS IN THE INTRODUCTORY STATISTICS CLASSROOM

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It is widely accepted that active learning and group work generally enhance learning in the statistics classroom, but how should those groups be formed? This study aims to better understand the characteristics of a productive team in the undergraduate introductory statistics course. Specifically, we explore the relationship between the attitudes of a student's teammates and that student's academic performance in both individual and group settings. We find moderate evidence that positive teammate attitudes towards statistics are associated with greater improvement from a student's individual to the team exam score. If we can better understand what combination of student characteristics results in productive teams, instructors can be intentional with how they form groups in the classroom, realizing the full efficacy of active learning.

INTRODUCTION

With their meta-analysis on the use of active learning in science, engineering, technology, and mathematics (STEM) courses, Freeman et al. (2014) cemented active learning's place in the classroom. Group work is one of the most common active learning techniques, playing a particularly large role in flipped classrooms—where "direct instruction moves from the group learning space to the individual learning space, and the resulting group space is transformed into a dynamic, interactive learning environment" (Flipped Learning Network, 2014, para. 1). For these techniques to be successful, however, forming functional and effective groups in these settings is essential.

There is established literature investigating peer effects in educational settings—how a student's peers influence their behavior, academic performance, and decision-making. Peer ability, peer gender, and peer race have all been shown to have an effect (e.g., Feld & Zölitz, 2017; Hill, 2017; Sacerdote, 2001). However, little is known about how peer attitudes, specifically those towards statistics, influence a student's progress in a course. Many studies have been done on how a student's attitude towards statistics relates to their individual academic performance (e.g., Sesé et al., 2015; Slootmaeckers, 2014; Sorge & Schau, 2002), but, to our knowledge, none have investigated how the attitudes of one's peers might affect individual and team performance. This study targets that gap.

Research repeatedly shows a positive correlation between student attitudes and their academic performance. For example, Sesé et al. (2015) found evidence that "students with better statistics performance should be those with more positive attitudes towards statistics" (p. 297). They go on to conclude: "Positive attitudes keep us using what we have learned. They also encourage us to seek opportunities to learn more. It is for these reasons that students' attitudes are the most important and influential outcome from introductory statistics courses" (pp. 298–299). Extending this idea, we hypothesize that students may benefit from working with peers who exhibit positive attitudes towards statistics.

In our approach to flipped learning, introductory statistics students at a large university engage in video lectures, reading assignments, and short online quizzes outside of the classroom; they then participate in teamwork activities during class time, guided by an instructor. Through validated instruments on a pre-course survey (administered within the first two weeks of the course), we measured each student's initial attitude towards statistics, background statistical knowledge, and demographics. Using mixed-effects models, we explored the relationship between individual student and team exam performance and the attitudes towards statistics among the student's team members.

METHODS

Our primary topic of interest is the relation between peer attitudes towards statistics in a team setting and students' academic performance. Data were collected and analyzed on 802 introductory statistics students in Spring 2018 across 19 different classrooms. Because we were interested in how a student's academic performance changes when working with peers, we asked students to complete the same exam problems, first individually and then in teams.

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The curriculum is divided into three units. At the beginning of each unit, students are randomly assigned into teams of three or four. Students work in their team during all class activities. At the end of the unit, students take an individual exam. During the class period following the individual exam, each team completes an "exam reflection" comprised of a subset of problems from the individual exam. Then, students are randomly assigned a new team for the next unit. During Unit One, students engaged in the following topics: basic probability, populations and samples, study bias, and statistical inference for one proportion. Topics in Unit Two included: study design, types of testing errors, statistical inference for one mean and for simple linear regression, and further reinforcement of Unit One topics. Both theory-based and simulation-based approaches to statistical inference were taught. Because the Unit Three exam was administered during finals week, students could not complete a team exam reflection after this final exam; thus, only data from Units One and Two are considered in this study.

Our primary explanatory variable of interest is the average attitude towards statistics among a student's team members (calculated excluding the student). We measured individual attitudes towards statistics with the Survey of Attitudes Toward Statistics (SATS-36), given in a pre-survey at the start of the semester. The SATS-36 is a 36-item Likert-type survey developed by Schau (2019), where each item allows for seven possible responses ranging from "strongly disagree" to "strongly agree." The instrument is grouped into six attitude components, summarized in Table 1, with 4–9 individual items per component. Responses to negatively worded questions are reversed, and an average is taken for each component so that higher attitude scores relate to more positive attitudes towards statistics. An overall SATS-36 score is computed by taking the average of the six attitude component scores.

Table 1. Six student attitudes towards statistics components measured in the SATS-36 instrument

Attitude Component	Brief Description
Affect	Feelings concerning statistics
Cognitive Competence	Attitudes about their knowledge/skills when applied to statistics
Value	Attitudes about the usefulness, relevance, and worth of statistics
Difficulty	Attitudes about the difficulty of statistics as a subject
Interest	Level of individual interest in statistics
Effort	Amount of work the student expends to learn statistics

The Comprehensive Assessment of Outcomes in a First Statistics course (CAOS) was also included on the pre-survey to assess students' statistical backgrounds coming into the course. Developed by a group of statistics education experts in 2004 (delMas et al., 2007), CAOS is comprised of 40 multiple choice questions that assess important learning outcomes for a first course in statistics, such as interpreting graphical displays of data and determining a study's scope of inference.

We tracked individual student progress in the course by their two midterm exam scores (ranging from 0 to 100). In the class period following each individual midterm exam, each team completed a single exam reflection; completion of this reflection counted as 8% of a student's combined exam score. To measure team performance in relation to an individual student, we calculated each student's normalized change (Marx & Cummings, 2007) between their team's exam reflection score (s_{team}) and that student's score on the same subset of questions on their individual exam (s_{indiv}):

$$\text{Normalized change} = \begin{cases} \dfrac{s_{team} - s_{indiv}}{100 - s_{indiv}} & s_{team} > s_{indiv} \\ \text{NA} & s_{team} = s_{indiv} = 0 \text{ or } 100 \\ 0 & s_{team} = s_{indiv} \\ \dfrac{s_{team} - s_{indiv}}{s_{indiv}} & s_{team} < s_{indiv} \end{cases}$$

As a measure of change in scores, normalized change has an advantage over a simple calculation of the difference between scores in that it adjusts for low-score bias. For example, if a student scores 95 on the individual exam, that student can only improve by at most 5, but a student who scores 50 on the individual exam could potentially double their score on the team exam reflection. Normalized change can be interpreted as the proportion of possible improvement/reduction in score the student achieved.

The normalized change in scores between the individual and team conditions captures how a student's score might change while actively working with their team. To investigate whether the characteristics of a student's team had any noticeable association with that student's individual academic performance after working with the team for an entire unit, we also fit models with the individual midterm exam score as the response. Because students took individual midterm exams and team exam reflections in both Units One and Two, we used a linear mixed-model approach. To account for the repeated measures on students and the correlation within teams, random effects for student and team were included in the models. The explanatory and control variables were modeled as fixed effects. Thus, the outcomes for student i in the jth team at the end of unit k are modeled as:

$$\text{NormalizedChange}_{ijk} = \boldsymbol{x}_{ijk}^T\beta + b_i + b_j + \epsilon_{ijk} \qquad \text{(Model 1)}$$

$$\text{ExamScore}_{ijk} = \boldsymbol{x}_{ijk}^T\beta + b_i + b_j + \epsilon_{ijk} \qquad \text{(Model 2)}$$

where $\text{NormalizedChange}_{ijk}$ is the normalized change in scores between the individual and team conditions, and ExamScore_{ijk} is the individual midterm exam score. The terms b_i, b_j, and ϵ_{ijk} are random effects for the student, team, and random error, respectively. The vector $\boldsymbol{x}_{ijk}$ represents the vector of explanatory and control variables measured on that student, summarized in Table 2.

Table 2. Variable descriptions

Role	Variable Name	Description
Response	exam_percent	Midterm exam score (0 to 100)
	exam_norm_diff	Normalized change (-1 to 1, as defined above)
Explanatory	team_Affect, team_Cognitive, team_Value, team_Difficulty, team_Interest, team_Effort	Average of teammate scores on each of the six SATS-36 components, excluding the student
	team_SATS	Average of teammate overall SATS-36 scores, excluding the student
Control	Affect, Cognitive, Value, Difficulty, Interest, Effort	Individual scores on each of the six SATS-36 components
	sex	Female, Male, or Other
	race	AIAN (American Indian Alaska Native), Asian, Black, Hispanic, Pacific, White, or Other
	CAOS	Pre-survey CAOS score
	team_sex	Proportion of shared sexual identities in a student's team with that student
	team_race	Proportion of shared racial identities in a student's team with that student
	team_CAOS	Average of teammate pre-survey CAOS scores, excluding the student

Note. Variables are recorded for each student. Some measure characteristics of the individual student, but others measure average characteristics of that student's teammates (excluding the student).

For each model, we fit both a base model using only team-level attitude variables in $\boldsymbol{x}_{ijk}$ and a full model that includes control variables in $\boldsymbol{x}_{ijk}$. Team attitude was calculated as the average attitude score among the student's team members (excluding the student), computed for each of the six attitude component scores and the overall SATS-36 score. Control variables included individual attitude, sex, race, and statistical background (CAOS), as well as team-level measures of these variables. Sex was recorded as one of three levels (male, female, and other); we defined team sex as the proportion of a student's teammates who share their self-identified sex. Similarly, team race was defined as the proportion of teammates of the same race as the student. Team statistical background was calculated by taking the average score on the CAOS test among the student's team members.

RESULTS

Only 686 of the 802 enrolled students completed the SATS-36 items on the pre-survey. After accounting for missing values in the control variables, we were left with 620 students and 1,046 observations (some students only completed one of the two midterm exams). The self-identified racial distribution of these students was 95.2% White, 1.8% Hispanic, 1.2% Asian, 1.0% Black, and less than 1% in each of the other racial categories. The students were almost equally split between males and females, with 51.4% self-identifying as female, 48.3% as male, and two students identifying as “other.”

Figure 1 displays plots of the normalized change between individual and team conditions versus average team overall attitude score, both by unit (a) and by individual exam score (b). Though the correlation between team attitude and normalized change is weak, there does appear to be a positive trend. The slope of the line for Unit 1 is greater than Unit 2, which is possibly because student attitudes towards statistics were measured at the start of the semester and could have changed throughout the semester. We also see that the slope of the line for students that scored in the 75–100th percentiles on their individual exams is greater than for students that scored in lower percentiles.

(a) (b)

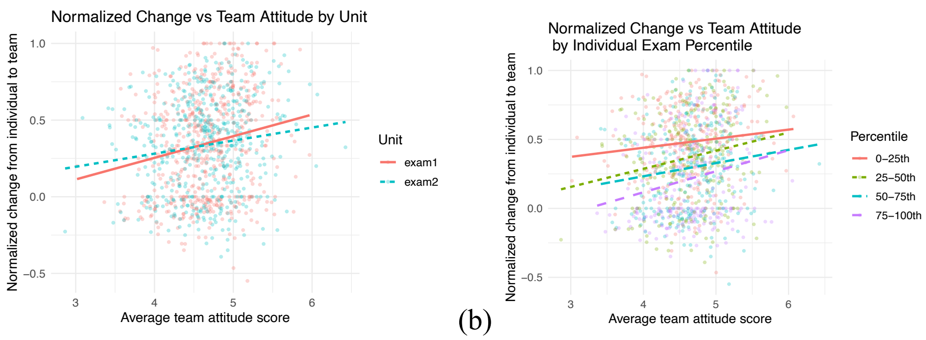

Figure 1. (a) Scatterplots of normalized change in scores against average team attitude score by unit and (b) by individual exam percentile

We first modeled a student’s normalized change between their individual and team scores using their team overall attitude score (team_SATS) as the primary predictor. Based on the exploratory plots shown above, we fit this model both with and without an interaction between team attitude and individual midterm exam score. Table 3 displays the base additive and interaction models (fit without including control variables).

Table 3. Fitted model coefficient summaries for normalized change (Model 1) on team overall attitude score, with and without interaction between exam score and team attitude (not including control variables)

	Base Model 1: Overall attitude				Base Model 1: Overall attitude with exam score interaction			
Model term	Estimate	SE	*p*-value		Estimate	SE	*p*-value	
(Intercept)	-0.199	0.100	0.047	*	1.860	0.339	<0.001	***
team_SATS	0.115	0.021	<0.001	***	-0.127	0.072	0.080	.
exam_percent					-0.026	0.005	<0.001	***
team_SATS:exam_percent					0.003	0.001	0.005	**

Results from the base additive model suggest that a one unit increase in team overall attitude towards statistics (on a 1–6 scale) is associated with between a 0.074 to 0.157 increase in normalized change (95% CI). That is, the estimated improvement from individual to team performance increases by between 7% to 16% as teammate positive attitudes towards statistics increase. However, the interaction model in Table 3 shows a statistically significant interaction between this change in normalized gain in scores and the individual student’s exam score ($p = 0.005$). Because the interaction coefficient is positive, this suggests that the improvement in normalized change associated with improved teammate attitudes towards statistics is greater among students that perform better on the individual exam. For example, among students who scored a 90 on their individual midterm exam, a one unit increase in average teammate attitude towards statistics is associated with an estimated 14.3% increase in students' normalized change in scores from individual to team conditions. In contrast, among students who scored a 60 on their individual midterm exam, a one unit increase in average teammate attitude towards statistics is only associated with an estimated 5.3% increase in students' normalized change. These estimated effects remain nearly the same when we control for individual attitude, sex, race, and statistical background and for team sex, team race, and team statistical background.

After examining the association between normalized change in scores and team overall attitude score, we considered the relationship between normalized change and each of the six separate team attitude component scores. We performed a backwards model selection procedure on the base Model 1 with normalized change as the response variable and the six average team attitude components as predictors; only the Cognitive Competence and Value team attitude components were statistically significant. Survey items such as "I can learn statistics" and "I will understand statistics equations" characterize the Cognitive Competence attitude component. Value involves attitudes towards the usefulness and relevance of statistics in students' studies and daily lives. Interactions between individual exam score and Cognitive Competence ($p = 0.244$) or Value ($p = 0.238$) were not significant. The resulting model, with and without control variables, is shown in Table 4. Without controlling for other variables, a one unit increase in average teammate Cognitive Competence towards statistics is associated with a 3.1% to 9.8% increase in normalized change (95% CI); this increase is smaller with average teammate Value towards statistics (95% CI [0.003, 0.069]). After we control for other characteristics, team Cognitive Competence continues to have a similar effect, but team Value is no longer statistically significant.

Table 4. Fitted model coefficient summaries for normalized change (Model 1) on Cognitive Competence and Value team attitude components, with and without control variables

	Base Model 1: Attitude components				Full Model 1: Attitude components			
Model term	Estimate	SE	p-value		Estimate	SE	p-value	
(Intercept)	-0.142	0.085	0.093	.	-0.769	0.335	0.022	*
team_Cognitive	0.064	0.017	<0.001	***	0.053	0.018	0.004	**
team_Value	0.036	0.017	0.035	*	0.010	0.018	0.585	
Affect					-0.005	0.018	0.765	
Cognitive					-0.002	0.021	0.941	
Value					-0.021	0.018	0.231	
Difficulty					0.022	0.020	0.278	
Interest					0.004	0.014	0.753	
Effort					0.006	0.013	0.617	
sexMale					0.021	0.021	0.326	
sexOther					-0.167	0.164	0.307	
raceAsian					0.647	0.310	0.037	*
raceBlack					0.690	0.311	0.027	*
raceOther					0.661	0.350	0.059	.
racePacific					0.674	0.348	0.053	.
raceWhite					0.649	0.300	0.031	*
CAOS					-0.003	0.001	0.005	**
team_sex					0.022	0.027	0.408	
team_race					-0.028	0.059	0.631	
team_CAOS					0.006	0.001	<0.001	***

When fitting Model 2 (using individual exam score as the response), we did not find any statistically significant coefficients among the team-level attitude measurements, either with or without including control variables. This suggests that teammate attitudes towards statistics do not have a significant association with how a student performs on an individual assessment after working with their team for several weeks during classroom activities.

DISCUSSION AND FUTURE WORK

Forming effective teams in an active learning classroom is key for student learning. Results from this study suggest that working with teammates that exhibit positive attitudes towards statistics—particularly those regarding their own statistical knowledge and skills—may boost students' academic performance while actively working with their team. Instructors could assign teammates that score high on the Cognitive Competence component of the SATS-36 instrument to students who may need additional academic support.

Because this study was conducted at a single university, our results are only reflective of student populations that are similar to the students in our study. Random assignment of teams eliminated the effect of self-selection into groups, so the attitudes of one's teammates could be considered randomly assigned. However, if a student rarely attended class or dropped the course, their teammates were merged into other teams to ensure all teams had at least three active members. Thus, it may not be entirely appropriate to make causal claims using our results. Additionally, student attitude was measured at the start of the semester and exams were not scored until later in the semester, so the measured student attitude scores would have been taken before team dynamics could have played a meaningful role in the development of a student's attitude towards statistics. Examining if team dynamics play a role in how students' attitudes towards statistics change over the course of the semester will be considered in future work.

Although there has been literature exploring peer effects of gender, academic ability, and more recently personality traits, how peer effects play a role in a student's attitude towards statistics is still an area that needs more attention. Understanding how team dynamics relate to student performance and development of a positive attitude towards statistics can help instructors enhance the learning environment in an active learning classroom through purposeful assignment of students into groups.

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