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Investigating the Impact of Team Composition, Self-Efficacy, and Test Anxiety on Student Performance and Perception of Collaborative Learning: A Hierarchical Linear Modeling Approach

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Introduction

A notable transition in higher education towards the adoption of active and collaborative learning approaches has been in progress for many decades [1][2]. The shift has been motivated by increasing evidence that these teaching methods can improve student engagement, motivation, and achievement in specific courses [3][4]. These approaches are very different from traditional lecture-based teaching methods, which mainly promote passive learning, where students are expected to passively absorb material through lectures and readings, and then they are evaluated individually [5]. The traditional approach has been especially difficult to sustain in engineering education, as students frequently struggle with complex concepts that require deep comprehension [5]. Furthermore, conventional lectures may not sufficiently prepare students to effectively utilize their knowledge and skills in practical situations [5]. The constraints of this approach have sparked a significant increase in enthusiasm for collaborative learning strategies in engineering education, in part aiming to tackle these difficulties and shortcomings [6][7].

Collaborative learning represents a pedagogical shift that encourages students to actively engage with their peers, working together in groups to solve problems, discuss ideas, and share knowledge [1][8]. While the literature provides a substantial body of evidence on how collaborative learning impacts student performance, there exists a persistent need for more nuanced research exploring how it affects constructs such as self-efficacy (SE), test anxiety (TA), and teamwork (TW) [9][10]. This gap is particularly salient when considering the diverse demographic factors that could influence collaborative learning outcomes [11].

The significance of this investigation was emphasized by the unexpected difficulties presented by the worldwide COVID-19 outbreak. The global epidemic compelled a sudden shift from conventional face-to-face instruction to online or hybrid methods of delivery, resulting in a substantial impact on education globally. According to [12], engineering students experienced reduced motivation and engagement in online courses compared to traditional face-to-face education. The pandemic more specifically had negative impacts on interaction and communication, especially in engineering courses conducted online [13].

Collaborative learning in engineering courses has been shown to bolster problem-solving skills, teamwork, and student engagement [8]. Several studies have also been carried out to examine how self-efficacy is affected by collaborative learning [9][10][14][15][16][17]. However, there is a notable lack of research in the current literature about the influence of collaborative learning on self-efficacy in team environments that focuses on the effects at the team level. This presents an opportunity for research to investigate the influence of team experience and team composition on constructs like SE, TA, and TW, including during the pandemic. Moreover, it raises intriguing questions, such as whether a student's performance is primarily connected to their individual self-efficacy or if the team's collective self-efficacy plays a role in influencing outcomes. This study aims to bridge these gaps, investigating the impact of collaborative learning on self-efficacy at both the individual and team levels, and within the context of online (Spring 2021) and socially distanced in-person (Fall 2021) settings for engineering courses during the COVID-19 pandemic.

To address these gaps in the literature, this study presents a comprehensive quantitative investigation conducted within the context of an introductory circuits course in electrical and computer engineering at a large Midwestern research university. Our research aims to shed light on the following key research questions:

1. How do student perceptions of the Collaborative Learning Experience (CLE) relate to key student outcomes such as test anxiety, self-efficacy, and course performance?
2. What role do student demographics (including gender, ethnicity, major, GPA, year in school, and prior circuit experience) and pre-existing perceptions of teamwork play in shaping both the CLE and student outcomes?
3. How does the composition of teams (considering factors like gender, ethnicity, major, GPA, prior circuit experience, and year in school) influence student perceptions of the CLE and, consequently, student outcomes?

To address these questions, we investigate the relationships in our survey data set through quantitative analysis, focusing on two dependent variables: student performance, in terms of their exam scores (Exam), and Collaborative Learning Experience (CLE), a measured variable from a survey questionnaire at the end of the semester about the student's perception of the collaborative learning experience. We in turn examine how these dependent variables may be affected by other collected measures, such as task and general self-efficacy, test anxiety, teamwork attitude, prior circuits experience, etc. As detailed below, we first examined the data to determine the degree to which there was clustering in the sample by student teams, namely by calculating interclass correlation coefficients. When there was little to no evidence of clustering, linear regression models were used to further analyze the data.
When the ICC uncovered significant team-level effects, which indicates significant clustering, Hierarchical Linear Modeling was utilized to conduct a more appropriate analysis of the data.

Literature Review

We begin by reviewing the findings of prior studies of self-efficacy, including its association with CLE and exam scores. Self-efficacy, defined as the belief in one's abilities to succeed in specific situations [18], plays a crucial role in collaborative learning environments. Studies have shown that individuals with high self-efficacy are more likely to contribute positively to group tasks, feel more comfortable engaging in complex problem-solving with peers, and persist longer in the face of difficulties [18][19]. For example, [20] found that students with higher self-efficacy were more active participants in collaborative groups, suggesting that self-efficacy enhances group learning experiences. Research also suggests that high self-efficacy can more generally enhance students' motivation and persistence with challenging tasks, leading to better performance outcomes [21]. Students with higher self-efficacy are additionally more likely to engage in effective study strategies and manage their time efficiently, resulting in better exam scores [18].

Research indicates that test anxiety, characterized by worry and tension related to assessment situations [22], can also significantly affect collaborative learning experiences. High levels of test anxiety can hinder students' ability to focus, communicate effectively, and contribute to group discussions, negatively impacting the collaborative learning process [23]. However, collaborative learning environments can also offer social support that helps reduce test anxiety through peer reassurance and shared coping strategies [24]. Research shows that test anxiety is inversely related to exam scores; as test anxiety increases, performance tends to decrease [25]. This relationship is partly due to cognitive interference caused by anxiety, which limits the mental resources available for focusing on and solving exam problems [25].

A positive attitude toward working in teams is another notable factor to consider, as it is associated with higher levels of engagement, mutual support, and collective effort toward learning goals [26]. Conversely, negative attitudes toward teamwork can lead to conflict, reduced participation, and lower group cohesion, undermining the collaborative learning process. Research by [27] demonstrates that teams with members holding a positive attitude towards collaboration outperform those with less favorable attitudes. Other studies have found that when students value and engage in effective teamwork, they are more likely to experience a deeper understanding and retention of the material, leading to better performance [26].

Having prior experience with learning materials can further shape collaborative learning experiences by influencing how individuals contribute to and benefit from group interactions. Prior knowledge can enable students to take on leadership roles within groups, guide discussions, and facilitate the learning of peers [28]. Furthermore, students with greater background knowledge are often more confident in their contributions, enhancing the overall effectiveness of the collaborative learning process [29]. This same paper stated that students with higher levels of prior knowledge tend to perform better on exams.

Exploring the complex array of variables outlined above may benefit from advanced analytic methods such as Hierarchical Linear Modeling (HLM). For example, [30] examined the impact of school climate (a team-level factor) on individual student outcomes, including academic performance. The paper synthesizes findings from studies that have used HLM to understand how broader educational environments influence student success. Also using HLM, [31] investigated the effects of collective responsibility for learning—a team-level factor—on academic achievement. Their findings suggest that students perform better in environments where teachers and students share a collective responsibility for learning outcomes. [32], as another example, applied HLM to explore how both direct (individual) and indirect (team-level) sources of social support from teachers, family, and friends influence the academic success of Latino middle school students. Their analysis revealed significant team-level effects, highlighting the importance of a supportive social context for student achievement. Finally, it is worth noting that HLM was used by [33] to examine the influence of personal and social-contextual factors at the individual and team level on K–12 academic performance. The results underscore the complex interplay between personal competence beliefs (like self-efficacy) and the social environment (classroom context) in affecting student learning outcomes.

Study Context

The investigation was conducted in a fundamental circuits course at a prominent Midwestern research university. The course encompassed technical mathematics and circuit-focused subjects, including linear resistive circuits, first-order linear circuits incorporating capacitors and inductors, analysis of linear circuits in a sinusoidal steady-state using complex numbers, magnetically coupled circuits and ideal transformers, as well as semiconductor circuits involving diodes and transistors. This course serves as an introductory course for students pursuing degrees in electrical and computer engineering. However, it is also a required course for students in other engineering disciplines such as mechanical engineering, industrial engineering, nuclear engineering, and multidisciplinary engineering. This results in a heterogeneous student body in terms of academic disciplines. The study gathered data from two consecutive semesters: spring 2021 and fall 2021. The importance of these two semesters was marked by the COVID-19 pandemic. The course was conducted entirely online during the spring of 2021, whereas in the fall of 2021, it was held in person with stringent COVID-19 protocols implemented within the university.

In this course, students work in teams of three or four to complete course assignments. Students are grouped into teams using several demographic variables (gender, ethnicity, prior circuits experience, major, etc.) to ensure that underrepresented students are not isolated and that student teams are relatively homogenous in terms of hands-on prior experience with circuits. Demographic information was collected using the Comprehensive Assessment of Team Member Effectiveness (CATME) teaming software. CATME is a web-based application developed by researchers at Purdue University to improve the effectiveness of student teams in collaborative learning environments [34]. Students were required to collectively complete thirteen weekly homework assignments and one group project in the collaborative learning framework. Additionally, students were encouraged to prepare for exams as a group. However, aside from this collaborative approach to coursework and study, students were required to individually complete two midterm exams and a final exam.

Participants and Data Collection

Pre- and post-course surveys were distributed to 751 students in spring 2021, resulting in 570 completed survey data pairs, and to 780 students in fall 2021, resulting in 429 complete pairs. The pre-survey was sent out during Week 2 of both semesters, and the post-survey was sent out during Week 15 of a 16-week regular semester course. Demographic data was gathered using the CATME system, which also facilitated the formation of student teams. As noted above, teams were assembled with consideration for students' availability for out-of-class meetings and certain demographic factors. CATME was configured to ensure no single gender or race was underrepresented within any group and teams were made with students with similar prior experience as the study suggests that disparities in experience levels can lead to issues like domination by more knowledgeable members, potentially sidelining less experienced students [35]. All data collection activities were carried out under a protocol approved by Purdue University’s Institutional Review Board (IRB).

Table 1 displays the descriptive statistics for each semester, including the demographic composition of the participants based on gender, race, and major. The participants were categorized as male or female; the remaining non-binary data points were very few and were therefore excluded from the analysis. The categorization of ethnicity included white and Asian groups, while other ethnicities were not sufficiently numerous to warrant separate distinctions. Therefore, these remaining ethnicities (Hispanic, black, native, and others) were combined to form an underrepresented minorities (URM) category. Most students in the spring semester were enrolled in the mechanical engineering (ME) major, whereas in the fall semester, a majority were pursuing degrees in electrical or computer engineering. This disciplinary distribution can be attributed to the way these courses are structured in the students' degree study plan. Industrial engineering (IE) was the next most popular major among the students who took this course, while the remaining majors were categorized as “other.”

Table 1: Descriptive Statistics by Semester

	Spring 2021				Fall 2021			
Gender	Male		Female		Male		Female	
	432		127		338		82	
Ethnicity	White	Asian		URM	White	Asian		URM
	292	94		156	220	40		147
Major	ECE	ME	IE	Other	ECE	ME	IE	Other
	123	342	74	23	292	65	51	16

Note: Not all participants completed all demographics questions, resulting in lower counts.

Measures

The pre- and post-surveys encompassed a range of measures drawn from existing literature, with modifications made to align them with the specific context of this study when deemed necessary. The self-efficacy, test anxiety, and teamwork attitude questionnaire were developed from [36] and [37]. The subsequent sections provide a summary of each measure. Confirmatory Factor Analysis (CFA) was performed on the collected data, confirming the distinctiveness of underlying factors and the effectiveness of individual questions within each item in gauging the corresponding factor for each measure. Additionally, reliability analyses were conducted for both pre- and post-survey data, and their outcomes are documented herein.

Self-Efficacy – General. An individual's belief in their ability to perform and succeed in a variety of different situations and contexts. The data collected was a 7-point Likert scale between “not true of me” and “very true of me.” The Cronbach’s alpha value for this measure for the pre-survey data was 0.91 and for the post-survey data, it was 0.94. Example question from the survey: “Compared with others in this class, I think I'm a good student.”

Self-Efficacy – Task. Students were surveyed to gauge their self-confidence in comprehending and mastering the content covered in the fundamental circuits course, encompassing areas such as linear resistive circuits, 1st order circuits, sinusoidal steady-state circuits, ideal transformers, and semiconductor circuits, including diodes and transistors. The data collected was based on a rating from 0-10, with 10 being most confident and 0 being no confidence. The dataset's reliability was assessed using SAS, yielding Cronbach's alpha values of 0.89 for the pre-survey and 0.87 for the post-survey. Examples from the survey include: “Rate your degree of confidence (i.e., belief in your current ability) to perform the following tasks by recording a number from 0 to 10.” One specific example of a task statement was: “Ability to analyze linear resistive circuits (using methods like nodal, mesh, source transformation, voltage current division, etc.).”

Task Anxiety. This construct refers to the anxiety individuals feel when confronted with academic tasks related to course content, such as reading, writing, or presenting information.

This anxiety can be detrimental to performance, motivation, and task engagement, as outlined by [38]. It should be distinguished from generalized test anxiety, which revolves around the testing process rather than the test's content. The data collected for this measure had the user rate their anxiety level between a range from 0-10. The pre-survey demonstrated a Cronbach's alpha of 0.94, while the post-survey yielded 0.92. Examples from the survey include: "Rate your degree of anxiety (how apprehensive you would be) to perform the following tasks by recording a number from 0 to 10." One such task was: "Ability to analyze linear resistive circuits (using methods like nodal, mesh, source transformation, voltage current division, etc.)"

Test Anxiety. Refers to feelings of fear, tension, or apprehension experienced by individuals when facing any kind of test or examination. This type of anxiety is not specific to a particular type of test or subject matter, but rather a general feeling of unease or worry related to taking tests or exams. The data collected for this measure was on a 7-point Likert scale between "not true of me" and "very true of me." The Cronbach's alpha value for the pre-survey was 0.88 and for the post-survey was 0.92. As a representative sample item from the survey stated: "I am so nervous during a test that I cannot remember facts I have learned."

Teamwork Attitude. This construct refers to an individual's positive or negative attitude towards working in a team or group setting. A person with a positive teamwork attitude is likely to be collaborative, supportive, and communicative in their interactions with others. On the other hand, a person with a negative teamwork attitude may be more likely to work independently, struggle with collaboration, and have difficulty communicating with others, according to [39]. The data for this measure was collected using a 4-point Likert scale ranging from "strongly disagree" to "strongly agree." The Cronbach's alpha value for the pre-survey was 0.69, and the post-survey was 0.68. This was a little lower than the desired 0.7 but was close enough to the desired value to be a potentially useful measure. As an example, a question from the survey: "I would rather work on team projects than on my own." Because we anticipated that differences amongst teammates could have an effect, the average teamwork attitude score was calculated for each team, along with the difference between each individual score and the team average.

Collaborative Learning Experience. Collaborative learning refers to an instructional approach in which learners work together in groups to achieve shared learning goals. It involves promoting interactions among students to enhance their cognitive and social development. Collaborative learning experiences can take various forms, such as group projects, peer-led discussions, and problem-solving tasks. The associated questions on the survey relate to how students perceived their collaborative learning experience in the course. This was only measured at the end of the semester. The data collected was on a 5-point Likert scale ranging from "strongly disagree" to "strongly agree." The Cronbach's alpha value for this post-survey measure was 0.88. Example questions from the survey include: "Collaborative learning helped me stay motivated in this class"; "Overall, the collaborative activities have enhanced my learning in this class."

GPA. The grade point average collected was self-reported by the students as part of the pre-course survey.

Prior experience. This asked students to rate their level of hands-on prior experience with solving circuits using a 5-point scale ranging from "None" to "Expert." Because we anticipated that differences amongst teammates could affect collaborative learning experiences, the average prior experience score was calculated for each team, along with the difference between the team average and each individual's score.

Team Average [of a variable]. This is the average value of a given variable or construct for all the students on a specific team.

Team Average [of a variable] Difference. This calculation involves subtracting the team's average score from an individual's score on a given variable. This measurement approach suggests that the significance of a given variable lies not only in the individual score but also in their score as it compares to their teammates' average scores.

Quantitative Models

In our quantitative analysis, we sought to examine the relationship between two dependent variables: collaborative learning beliefs or experiences (CLE) and student performance, as measured by individual exam scores (Exam). We aimed to understand how these variables related to both demographic control variables and experimental variables derived from the survey data.

In order to carry out such analyses it is important to also consider the intraclass correlation coefficient (ICC), a statistical measure used to determine the degree of clustering in a sample. To compute the ICC for a sample, the total variance of the dependent variable can be partitioned into variance within groups and variance between groups. Therefore, the ICC is a ratio that compares the variance between groups to the total variance. In other words, the ICC is essentially a measure of the degree to which individuals within the same groups resemble each other, which violates one of the assumptions of traditional linear regression and thus necessitates a regression method that accounts for clustering within a sample. ICC values can range from 0 to 1, with higher values indicating stronger intergroup correlations and indicating the need for Hierarchical Linear Modeling (HLM) methods. While the interpretation of ICC depends on the context of the study and the research question being addressed, ICC values greater than 0.1 generally indicate that there is a significant amount of clustering in the data and that HLM may be appropriate [40]. It is also important to note that the interpretation of ICC values should be done in conjunction with other information about the study, such as the sample size and characteristics, the instrument(s) used, and the research question(s).

Interestingly, when considering collaborative learning beliefs or experiences (CLE), we found limited team-level significance when accounting for control and experimental variables (ICC = 0.05). Consequently, we conducted a stepwise multivariate linear regression analysis. This analysis proceeded in two steps (See Eq 1 and Eq2). The initial model involved only the control variables, including gender, race, major, and semester. In the second model, we included both the control variables and experimental variables, encompassing GPA, prior experiences, teamwork attitude, task anxiety, test anxiety, and general self-efficacy. Notably, during this analysis, we identified potential multicollinearity between general self-efficacy and task self-efficacy, leading us to utilize only general self-efficacy in our model and exclude task self-efficacy.

Model 1: Model with Control Variables.

$$CLE = \beta_0 + \beta_1(Gender) + \beta_2(Race) + \beta_3(Major) + \beta_4(Semester) + e_i \quad \text{(Eq 1)}$$

where e_i is the error term.

Model 2: Model with Control and Experimental Variables.

$$CLE = \beta_0 + \beta_1(Gender) + \beta_2(Race) + \beta_3(Major) + \beta_4(Semester) + \beta_5(GPA) + \cdots + e_i \quad \text{(Eq 2)}$$

where e_i is the error term.

Regarding the dependent variable "Exam," we conducted stepwise HLM to account for the observed substantial team-level effects that could predict student's exam score (ICC = 0.29). HLM is a statistical approach for modeling data that involves nested structures, where lower-level units of analysis are nested within higher-level units. HLM is particularly useful for analyzing data in educational and social science research where data are often nested within individuals, classrooms, schools, or other hierarchical structures. HLM allows for modeling both fixed and random effects. Fixed effects are constants that are assumed to be the same for all groups or individuals in a sample. In contrast, random effects vary between groups or individuals, and their variation is modeled as a distribution. The HLM models used in this analysis incorporate both fixed and random effects, allowing for the examination of individual and group-level variation simultaneously. Finally, in this study, HLM parameters were fitted using full information maximum likelihood estimation which can be used to model complex data structures and data with missing values.

The HLM models used in this analysis assume that student performance (i.e., exam score) is a function of both individual-level predictors and group-level predictors. The following three models represent the HLM models that were fit. Model 1 is the null value model (Eq 3), which is used to examine the individual and group-level variance in the data and compute ICC. The null value model also provides a starting point for assessing whether more complex models provide more information to explain the variance at each level.

$$\begin{aligned} Exam &= \beta_{0j} + r_{ij} \\ \beta_{0j} &= \gamma_{00} + u_{0j} \end{aligned} \quad \text{(Eq 3)}$$

where r_{ij} =student level error, and u_{0j} = team level error.

Model 2 is a random intercept model fit with control variables (Eq 4). This model allows researchers to assess the impact of control variables, such as demographic variables, on the outcome variable. This model allows for comparisons to models that contain the experimental variables to help assess the significance and magnitude of the effects while controlling for other factors.

$$\begin{aligned} Exam &= \beta_{0j} + \beta_{1j}(Gender) + \beta_{2j}(Race) + \beta_{3j}(Major) + r_{ij} \\ \beta_{0j} &= \gamma_{00} + \gamma_{01}(Semester) + u_{0j} \end{aligned} \quad \text{(Eq 4)}$$

where r_{ij} = student-level error, and u_{0j} = team-level error.

Model 3 is a random intercept model fit using both experimental and control variables (Eq 5). This allows researchers to examine the significance and magnitude of the effects of experimental variables manipulations while controlling for other variables. This type of model is valuable for investigating the effects of interventions or treatments while controlling for individual differences and group-level variation. Modeling the data is a stepwise manner helps disentangle the effects of individual characteristics from any variability between groups, providing a more nuanced understanding of the factors influencing the outcome.

$$
\begin{aligned}
Exam = {} & \beta_{0j} + \beta_{1j}(Gender) + \beta_{2j}(Race) + \beta_{3j}(Major) + \beta_{4j}(GPA) + \beta_{5j}(Task\ Anxiety) \\
& + \beta_{6j}(Task\ Efficacy) + \beta_{7j}(Test\ Anxiety) + \beta_{8j}(Team\ Dif\ Experience) \\
& + \beta_{9j}(Team\ Dif\ TW\ Attitude) + r_{ij} \\
\beta_{0j} = {} & \gamma_{00} + \gamma_{01}(Semester) + \gamma_{02}(Team\ Mean\ Experience) + \\
& \gamma_{03}(Team\ Mean\ TW\ Attitude) + u_{0j} \qquad \text{(Eq 5)}
\end{aligned}
$$

where r_{ij} = student-level error, and u_{0j} = team-level error.

Results

The descriptive statistics of the measures are presented in Table 2 and the correlation matrix is shown in Table 3. As can be seen in Table 3, the measures used as independent variables in the regression models tend to have relatively low intercorrelations. Further analysis indicates that these variables do not demonstrate multicollinearity for any of the regression models presented.

Table 2: Descriptive Statistics for Selected Measures

	Spring 2021			Fall 2021		
	N	Mean	SD	N	Mean	SD
GPA	570	3.39	0.45	427	3.50	0.40
Team Avg Prior Experience	568	2.76	0.86	424	3.01	0.75
Prior Experience Difference	562	0.00	0.57	424	0.00	0.65
Team Avg Teamwork Attitude	570	15.63	1.00	429	15.24	1.30
Teamwork Attitude Difference	570	0.00	1.46	429	0.00	1.27
Task Anxiety	570	26.23	9.27	429	26.06	10.28
Test Anxiety	570	17.38	5.83	429	17.30	5.53
Gen SE	570	42.52	8.11	429	41.03	8.73
Task SE	570	51.20	12.93	429	47.38	14.82

Note: There are a few missing values due to incomplete data submitted by students

Table 3: Correlation Matrix of the Measures

	Avg Experience	Experience Diff	Avg Team Attitude	Team Attitude Diff	Task Anxiety	Test Anxiety	General SE	Task SE
GPA	-0.06	-0.01	-0.05	-0.11	-0.15	-0.23	0.32	0.08
Avg Experience	--	0.00	-0.03	0.00	-0.12	-0.05	0.05	0.06
Experience Diff		---	0.00	0.02	-0.11	-0.13	0.10	0.08
Avg Team Attitude			---	0.00	-0.03	-0.01	0.06	-0.004
Team Attitude Diff				---	0.001	-0.03	-0.01	0.01
Task Anxiety					--	0.50	-0.44	-0.38
Test Anxiety						--	-0.41	-0.22
General SE							--	0.52

Table 4:
Stepwise Multivariate Regression Results for Collaborative Learning Beliefs (CLE)

	Model 1			Model 2		
Variable Name	**B Coefficient**	***F*(1, 925)**	***p***	**B Coefficient**	***F*(1, 927)**	***p***
Gender (Male)	-0.16	0.19		0.22	0.36	
Race (Asian)	1.04	9.06	**	1.30	17.81	***
Race (URM)	0.19	0.17		0.07	0.03	
Major (ME)	-1.47	13.99	**	-1.50	17.89	***
Major (IE)	-0.75	2.07		-1.08	5.24	*
Major (Other)	-1.01	1.59		-1.10	2.43	
Semester (Fall 2021)	-1.23	11.63	**	-0.42	1.56	
GPA				-0.74	4.12	*
Avg Prior Experience				-0.48	7.90	***
Prior Experience Dif				-0.33	2.02	
Avg Teamwork Attitude				1.36	124.55	***
Teamwork Attitude Dif				1.12	127.46	***
Task Anxiety				-0.01	0.04	
Test Anxiety				0.08	6.92	**
Gen SE				0.05	7.10	**
R^2	0.03			0.26		

Note: Comparison groups: Gender (Female), Race (White), Major (ECE), Semester (Spring 2021) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

The results of the stepwise multivariate linear regression are shown in Table 4. By comparing the R^2 values, it is apparent that Model 2 explains more variance than Model 1, indicating that the experimental independent variables are potentially useful for predicting student beliefs about collaborative learning experiences. The results of Model 2 indicate that gender does not predict collaborative learning beliefs; however, both ethnicity and major potentially do for this sample. Compared to white students, Asian students have greater collaborative learning beliefs. In addition, Mechanical Engineering and Industrial Engineering students tend to have lower collaborative learning beliefs compared to Electrical and Computer Engineering students.

Additionally, higher self-efficacy was related to greater collaborative learning beliefs. Yet paradoxically, higher GPA and greater prior experience were related to lower collaborative learning beliefs. Higher collaborative learning beliefs were also correlated with higher test anxiety but were not related to task anxiety. In other words, anxiety about being assessed was related to more positive views about collaborative learning, but anxiety about the specific topic covered in the course was not related to collaborative learning beliefs. Interestingly, not only did attitudes towards teamwork (i.e., Avg Teamwork Attitude) predict collaborative learning beliefs, but the difference in attitude between the individual and their team also predicted collaborative learning beliefs. In other words, it is not just a team member's attitude towards teamwork, but how their teamwork attitude compared to their teammates that was important for predicting collaborative learning beliefs.

The results of the stepwise HLM model are shown in Table 5. Examining the random effects in Model 1 we see that both individual variance and team-level variance are significant, indicating that an HLM approach is appropriate for modeling this data. Examining the random effects in Model 2, we note that the team-level variance can mostly be explained based on demographic details. Finally, examining random effects in Model 2, we note that the experimental variables can explain some of the individual-level variance. However, a significant amount of variance is left to be explained by factors not included in the model. Because meaningful R^2 values cannot be estimated with HLM models, the model fit is evaluated by comparing the Akaike Information Criteria (AIC) and the Bayes Information Criteria (BIC) of the nested models. For both AIC and BIC, lower scores indicate greater model fit. As can be seen in Table 5, Model 3 results in the lowest AIC and BIC values, and we therefore interpret the exam score using Model 3.

Unsurprisingly, the results indicate that students enrolled in the spring semester score higher on the exam than students enrolled in the fall. In addition, students with higher GPAs scored higher on the exam. Happily, we found that differences in exam scores were not related to gender or race when controlling for the other variables in Model 3. In terms of the specific variables of interest in this study, test anxiety was negatively related to exam scores while task anxiety was not related to exam scores. Similar to collaborative learning beliefs, anxiety about being assessed rather than anxiety about the specific topics was related to exam performance. Likewise, students with higher levels of general self-efficacy were predicted to earn higher exam scores.

Interestingly, teamwork attitudes were negatively related to exam scores, but this relationship was found only when examining individual minus the team differences instead of just the individual score. In other words, having more favorable teamwork attitudes as compared to one's teammates predicted lower exam scores. However, the team average of teamwork attitudes did not significantly predict exam scores, meaning that the overall teamwork attitude may be less important than the differences between team members. Finally, prior experience with circuits was not related to exam scores.

Table 5:
Stepwise Multivariate Hierarchical Linear Modeling Results for Total Exam Points

	Model 1			**Model 2**			**Model 3**		
Variable Name	**Coefficient**	***t*-value**	***p***	**Coefficient**	***t*-value**	***p***	**Coefficient**	***t*-value**	***p***
Exam (intercept)	63.69	80.84	***	60.02	39.50	***	8.42	0.40	
Gender (Male)				4.57	3.45	***	1.02	0.87	
Race (Asian)				0.18	0.15		0.15	0.15	
Race (URM)				1.82	1.12		1.34	1.01	
Major (ME)				3.81	2.77	**	3.59	3.14	**
Major (IE)				-3.92	2.15	*	0.14	0.10	
Major (Other)				2.42	0.86		1.76	0.44	
Semester (Fall 2021)				-19.78	15.50	***	-19.56	17.95	***
GPA							10.37	8.89	***
Prior Experience Difference							-0.46	0.61	
Team Avg Prior Experience							-0.75	1.35	
Teamwork Attitude Difference							-0.97	3.04	**
Team Avg Teamwork Attitude							0.41	1.03	
Task Anxiety							0.07	1.29	
Test Anxiety							-0.39	4.10	***
General Self-Efficacy							0.76	11.93	***
Random-Effects	**Variance component**		***p***	**Variance component**		***p***	**Variance component**		***p***
Team-level effect (u_{0j})	117.33		***	3.28			1.13		
Student-level effect (r_{ij})	285.04		***	269.99		***	178.51		***
ICC	.29								
AIC	8758.6			8003.6			7607.1		
BIC	8770.3			8042.6			7611.4		

Note: *** p < 0.001, ** p < 0.01, * p < 0.05

Discussion and Conclusion

In this section, we review some of the most notable results from the preceding analysis, including further interpretation of the results, and propose some possible explanations. Beginning with demographic variables, Asian students reported stronger beliefs in the value of collaborative learning compared to white students. This may reflect cultural differences in learning styles, or the value placed on group harmony and collective effort. Additionally, Mechanical Engineering (ME) and Industrial Engineering (IE) students showed lower collaborative learning beliefs compared to their counterparts in Electrical and Computer Engineering (ECE). These findings suggest that there may be disciplinary differences in the value and integration of collaborative learning in different degree programs.

Turning to other variables of interest, we find evidence of a positive relationship between self-efficacy (SE) and collaborative learning beliefs. Students reporting higher self-efficacy, who more strongly believe in their ability to succeed in tasks, also tend to have greater faith in the value of collaborative learning. This makes some intuitive sense, as higher self-efficacy could lead to a greater willingness to engage with others and a belief in the positive outcomes of such engagements. However, students with higher GPAs and more prior experience showed lower collaborative learning beliefs. One possible interpretation is that students who are academically stronger or more experienced may feel less need for collaborative learning, as they might be more confident in their learning strategies. Students with higher collaborative learning beliefs also reported higher test anxiety but not higher task anxiety. This suggests that students who are anxious about exams might place more value on collaborative learning, possibly viewing it as a strategy to improve their performance or as a support system. The average teamwork attitude within the team is another observed predictor of collaborative learning beliefs, but even more telling is the difference in teamwork attitude between the individual and their team. If an individual's attitude toward teamwork differs significantly from their team's average, this may significantly influence their belief in the effectiveness of collaborative learning. This highlights the importance of team dynamics; it is not merely the overall attitude of the team that matters, but rather how well-matched the team members are in their views on collaboration.

It is also worth noting that students in the spring semester performed better than those in the fall, which could be due to a variety of factors not explored in this study, such as differences in instructional methods online versus in-person, and less stress taking exams from home versus a carefully controlled common exam situation with COVID-19 protocols. Further, test anxiety was found to negatively impact exam scores, while task anxiety did not have a relationship with exam performance. This may suggest that the stress of being evaluated has a detrimental effect on exam outcomes, but anxiety specific to the course material does not. Higher general self-efficacy predicted better exam performance, aligning with the literature that associates self-confidence with academic achievement. An unexpected finding was the negative relationship between individual-team differences in teamwork attitudes and exam scores. This suggests that a mismatch in teamwork attitudes within a team correlates with lower individual exam scores. However, the average teamwork attitude across the team was not a significant predictor of exam scores, suggesting that individual perceptions relative to the team are more critical than the team's overall sentiment. Prior experience with circuits also did not predict exam scores, which could imply that the course effectively leveled the playing field for students with varying backgrounds, or that other factors were more influential in determining exam performance.

These results address the core research questions proposed, revealing possible connections between Collaborative Learning Beliefs or Experience (CLE) and student performance (Exam) with various control demographic factors as well as other experimental variables measured. Furthermore, our findings indicate that the team composition significantly influences the outcomes, highlighting the potential impacts of contrasts between an individual's attitudes and their team's average attitudes. Although we have hypothesized certain explanations for these relationships, additional qualitative research is necessary to validate these hypotheses. Future studies, perhaps employing open-ended survey questions or interviews with students, could be invaluable in deepening our understanding of these dynamics.

Limitations

Educational research, particularly when implementing interventions in large, established courses, inherently faces some constraints. Conducting this study within a single institution may limit the generalizability of the findings, as it may not represent the diversity of experiences across different universities, cultures, or educational systems. The unexplained variance in individual outcomes also suggests that other influential factors might not be captured in the current model, such as personality traits, prior group work experiences, or external stressors. The study acknowledges the importance of team composition but does not deeply explore the specific dynamics within teams that may influence learning outcomes, such as leadership roles, conflict resolution strategies, or communication patterns. The study also lacks qualitative data that could provide a richer understanding of students' experiences with collaborative learning and the context behind the quantitative findings. The COVID-19 pandemic may have had unforeseen effects on student learning and could make it difficult to apply the findings to non-pandemic teaching and learning contexts. Moreover, this study was conducted exclusively during semesters impacted by the pandemic, complicating efforts to discern how the pandemic might have influenced the results, as we lack comparative data collected during a non-pandemic semester.

Future Research

As noted above, qualitative methods, such as interviews or focus groups, could provide more nuanced insights regarding students' perceptions and experiences of collaborative learning, including possible explanations for some of the quantitative findings presented above. Future studies could also include a wider range of institutions, including those with different student demographics, to enhance the external validity of the findings. As the educational landscape has largely normalized post-pandemic, it will be important to reassess the impact of collaborative learning in the current context. Collaborative studies across disciplines could additionally reveal how different fields might uniquely benefit from or challenge collaborative learning methods.

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