In-Person vs Blended Learning: An Examination of Grades, Attendance, Peer Support, Competitiveness, and Belonging

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ABSTRACT

Since March of 2020, universities around the world have offered remote versions of courses to help limit the spread of COVID-19. Two years later, in the Spring 2022 quarter, the lectures in the CS1 course at our large, public research-intensive university were taught via two modalities—an in-person modality in which students attended traditional, in-person lectures and a blended modality in which students attended a remote lecture on Zoom. Every other course component—labs, discussions, office hours—were held in-person for both groups. The unique setup of the CS1 course allowed us to perform a comparative analysis of the outcomes and attitudes between the two groups. In this paper, we analyze the difference in course outcomes, peer support, competitive feelings in class, and students' sense of belonging between the groups. Our results indicate that students in the blended learning group attended lectures more frequently than their in-person counterparts yet performed 4-7% *worse* on the midterm and final exams. The blended learning group also experienced significantly *less* feelings of competitiveness than their in-person counterparts. Interestingly, we discovered a consistent trend among our results indicating that the gap in grades, peer support, and classroom competitiveness between the blended group and in-person group was more pronounced among first- and second-year undergraduates than third- and four-year students. Despite the two learning groups having different instructors, our results shed light on the potential advantages and drawbacks of a blended learning experience in CS1 that instructors should consider when deciding on the format of their course.

CCS CONCEPTS

• **Social and professional topics → CS1**.

KEYWORDS

blended learning, hybrid learning, sense of belonging, competitiveness, peer support, student outcomes

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1 INTRODUCTION

The COVID-19 pandemic disrupted the traditional, in-person classroom experience [37]. Universities around the world transitioned to a fully online learning environment [6, 34], leading to mostly negative impacts on students' learning [7, 15]. Though the peak of the pandemic has passed, many institutions have chosen to offer a *blended* learning environment to their students, which combines in-person and remote activities [5, 9]. In fact, some works have referred to blended learning as "the new normal" [29] and others have explicitly called for studies to explore the combination of remote and in-person classroom experiences [6]. Blended learning may be an effective way to increase accessibility of CS courses while maintaining high-quality instruction in computer science courses, which have seen high enrollment across universities [3, 35]. However, before adopting a blended learning design in computing courses, our research community should fully understand the impact of a blended learning experience on student attitudes and outcomes.

In Spring 2022, our large, public research-intensive university offered the introductory computer science (CS1) course via two modalities: blended learning and in-person learning. Both groups were required to attend an in-person lab and had the option to attend open office hours and a discussion section in-person. However, the blended learning group completed two 80-minute lectures remotely via Zoom while the in-person learning group attended the lectures in-person every week.

The conditions of this CS1 course offer a valuable data point in the continuing line of work to evaluate the effectiveness of blended learning. During the quarter, we collected students' grades and attendance data and asked students to self-report the number of peers they could work with, their feelings of competitiveness, and their sense of belonging in the course in order to answer the following research questions:

Compared to an in-person modality, how does a blended instructional modality impact:

(1) students' **attendance** in lectures in a CS1 class?
(2) students' **grades** on assignments and exams in a CS1 class?
(3) the **number of peers** that students reach out to in a CS1 class?
(4) students' **feelings of competitiveness** in a CS1 class?
(5) students' **sense of belonging** in a CS1 class?

2 RELATED WORK

2.1 Outcomes of In-Person vs. Blended Learning

"Blended learning" can describe any combination of in-person and remote activities [9, 29]. Therefore, the set of related work that discusses a "blended learning environment" can refer to a potentially wide array of learning settings. Based on our literature search, the current work regarding the effect of blended learning on outcomes is divided, with studies finding both positive [27] and negative [23] learning outcomes. However, research indicates that a variety of factors such as course design, access to resources, and length of instruction may be important factors in the effectiveness of the experience [19, 27].

In the computing education research space, the most similar work to ours is a very recent study from Gulati et al [14]. The authors analyzed student outcomes and sense of belonging between in-person sections and a fully-online sections of the same upper-division course and found that the online sections performed just as well as the in-person group on quizzes and the final exam without experiencing less sense of belonging [14]. Similarly, Förster et al. present findings from an introductory computer science course taught in a blended learning environment [12]. Ultimately, the authors found insignificant differences between exam scores, although more students in the blended-learning group undertook bachelor projects and fewer students dropped the course. Similarly, a study by Yigit et al. showed that in comparison to an in-person model, a blended learning approach resulted in similar assignment grades; however, the students in the in-person model displayed markedly higher exam scores [38].

2.2 Peer Support and Interaction

A student's interaction with their peers and classmates plays a vital role in that student's satisfaction, persistence, and outcomes. At a high level, Tinto's student integration model informs us that greater social and academic integration produce more commitment and persistence from students [36]. Empirically, a 2001 study of distance education by Graham and Scarborough found that 64% of students felt that having a group of peers to work with was a benefit to their learning [13]. However, recent studies that examine the effect of distance learning due to COVID-19 found that students felt less connected to peers and couldn't reflect on progress with classmates [2, 21]. Therefore, we hypothesize that students in the blended learning group may feel less connected to their peers, which may have a detrimental impact on their learning.

2.3 Competitiveness in the Classroom

We were not able to find any studies that compared the effect of a blended or remote learning experience on students' feelings of competition. However, work from Barker et al. describes how communication patterns in computer science classrooms can promote a "defensive climate" where an informal student hierarchy is established and some students "show-off" their knowledge in front of the class based on question wording [4]. More work has been done to investigate the impact of classroom competition on student learning, with current findings showing mixed impacts of classroom competition. Meece et al. noted that competition can increase the academic achievement for some students, but it can also have a chilling effect on students' motivation [28]. Indeed, Canning et al. point out that classroom competition is an often overlooked factor that can hinder first-generation student performance, engagement, and retention in STEM courses [8], illustrating the chilling effect discussed by Meece et al.. In a similar vein, a study on Hong Kong students by Lam et al. found that students in a competitive environment performed better on easier tasks, but were also more critical of themselves during self-evaluation [24]. These studies exemplify the dual impacts of competitiveness in the classroom: while it may serve to improve some students' outcomes, it may be a barrier to persistence for others.

2.4 Sense of Belonging

Previous studies point out several factors that can influence a students' sense of belonging [11, 18, 22, 25]. Freeman et al. found associations between a student's sense of belonging and factors such as the instructor's openness to student participation, organization of the course, and a student's own self-efficacy [11]. While these are factors that can be somewhat controlled by the instructor and course environment, Lewis et al. found that students who have communal goal orientations of computing, which means that they hope to work for the benefit of others, tend to have lower sense of belonging, unless they view computing as a tool to advance communal goals [25]. Regardless of the extent to which a course can impact sense of belonging, it is shown to relate to academic outcomes and persistence in computing [22]. However, we found few studies in computing education that examine the impact of different modalities on students' sense of belonging.

3 METHODS

3.1 Course Setup

We conducted the study at a research-intensive public university in a CS1 course. In Spring 2022, we offered the lectures for this course in two settings: (1) remote and (2) in-person. There were four lecture sections offered in this course; two of them were taught remotely via Zoom and the other two were taught in-person. The similarities between the two modalities are as follows:

- All lectures covered the same content with the same slides and same coding examples.
- All lectures met twice a week in 80-minute lecture sessions on Tuesdays and Thursdays.
- All lectures included a peer instruction [33] component where students completed short participation activities on Google Forms and discussed with classmates (either with a person seated nearby or in a Zoom breakout room).
- All students were required to attend an in-person lab section for 50 minutes per week.
- All students were required to complete the same assignments and readings.

- All students were required to complete a remote midterm exam and remote final exam.
- All students could optionally attend an in-person discussion for 50 minutes per week.
- All students could optionally receive help in assignments by attending tutor hours and office hours remotely or in-person.
- All students could engage in pair programming [31] when completing their programming assignments.

The key differences between the two modalities are as follows:

- The two remote lectures were taught one by instructor and the two in-person lectures were taught by a different instructor. The instructor of the remote lectures was a 3rd year professor having taught this course 3 times and the instructor of the in-person lectures was a 1st year professor having never taught this course before.
- The two remote lecture sections were held at 9:30 AM and 11:00 AM while the in-person lecture sections were taught at 2:00 PM and 3:30 PM, although all lectures were on Tuesdays and Thursdays.

Of course, there are threats related to the differences of these courses, which we explain further in Section 5.2.

3.2 Participants

Per our approved Human Subjects protocol, we obtained consent from students to use their course data. In total, 380 students consented to providing survey data to the research team—199 from the blended group and 181 from the in-person group. As seen in Table 1, we had a large disparity based on university standing in the distribution of students in the two lecture sections, with the in-person lecture having far more first- and second-year students.

Table 1: Comparison of student populations between in-person and blended learning group

	First Year	Second Year	Third Year	Fourth Year
Blended	10	52	62	73
In-Person	41	106	19	15

We gave a pre-term survey to students to learn about who our students were and why they were taking the course. In the blended learning group, 75% of students had no prior programming experience, whereas 70% of students in the in-person group had no prior programming experience. The top three self-identified racial groups among both learning groups were similar, with roughly the top three groups being Asian (55%), White (16%), and Latinx (16%). The remaining students self-identified into groups of less than 10 students, so we refrain from reporting those.

The majority of the students were *not* majoring in computer science. Of the 372 consenting students that completed the pre-term survey, only 12 (3.2%) reported being Computer Science majors. The most popular majors among our students include Psychology, Cognitive Science, Biology, and Mathematics. However, many of these majors include a coursework requirement that is satisfied by our CS1 course. As a result, 243 (65.3%) of the 372 students said that they are taking the course to fulfill a major or minor requirement, 71 of the students reported taking the course out of interest in computer science, 24 took the course to fulfill an elective requirement, and 18 took the course to switch into the Computer Science major. The remaining responses were custom options typed-out by students (as opposed to selecting one of the provided options).

3.3 Data Collection

3.3.1 Lecture Attendance. Students completed short participation activities on Google Forms each lecture. The forms were only able to be accessed by scanning a QR code or visiting a unique link that was only shared live during the lectures. While it is possible for students to send the link to a friend during class, our research team believes this occurred very rarely as the lecture attendance typically matched our estimate based on observing the number of students each lecture on Zoom or in-person. Therefore, we felt confident using the Google Form response data to calculate the lecture attendance.

3.3.2 Student Grades. Student completed 8 weekly programming assignments (PAs), one midterm exam, and one final exam. Both exams were administered remotely and were released to all students at the same time, with a 72 hour time frame to complete the 3 hour exam. Once students started the exam, they had three hours to submit it. Both exams included multiple-choice questions, free-response questions, a programming task on an online IDE called EdStem [10], and required a video explanation from students of their code for the programming task. Students received a grade out of 100 for each exam. For the programming assignment outcomes, we calculated the average of all the PAs after dropping the lowest score, following the class policy of dropping the lowest PA.

3.3.3 Weekly Surveys. Students answered a weekly survey each time they submitted a programming assignment, meaning we had up to 8 responses from each student for the following questions. As an incentive, students were awarded one out of 100 points on their programming assignment for completing the survey. In each survey, we included the same questions about peer support, classroom competitiveness, and sense of belonging.

Question about Peer Support (PS)

Students provided a free-response answer to the question below:

- **PS1:** At this time, approximately how many students in this course would you be comfortable reaching out to study with?

We used regular expression matching to detect all numbers in a response and parsed the responses for textual representation of numbers ("one", "two", etc). We used the lower end of the range for consistency when students gave a range of numbers (e.g., "3-5"),

Questions about Classroom Competition (CC)

We used two survey questions that we felt represented feelings of competition in a class environment. These questions have been used at our institution since the pandemic to understand students' attitudes and were part of a prior work related to emergency remote teaching [26]. Each week, students rated their agreement on a scale from 1 (not at all) to 5 (significantly) with the following questions:

- **CC1:** I feel I am competing with other students in this class.
- **CC2:** Students in this class like to show off their knowledge.

Questions about Sense of Belonging (SB)

Our questions come from Krause-Levy et al. [22] and Agarwal et al. [1], who previously examined sense of belonging in computing courses. Each week, students rated their agreement on a scale from 1 (not at all) to 5 (significantly) with the following questions:

- **SB1:** I feel accepted in this class
- **SB2:** I feel comfortable in this class
- **SB3:** I feel supported in this class
- **SB4:** I feel like I don't belong in this class

3.4 Data Analysis

We conducted a series of statistical tests to detect differences in grades, lecture attendance, peer support, classroom competitiveness, and sense of belonging. For peer support, competitiveness, and belonging, we had up to 8 responses per student. For each student, we calculated the average of the responses they submitted to arrive at a single statistic for each student (i.e., if a student submitted 7 weekly surveys, we took the average of the 7 responses related to peer support, competitiveness, and belonging).

As mentioned in Section 3.2, the lecture sections differed in the distribution of students according to university standing. While the in-person lecture had a majority of first- and second-year students, the remote lecture had a majority of third- and fourth-year students. Therefore, we conducted an ANCOVA (Analysis of Covariance) to detect the effect of the lecture type *while accounting for* students' year in university (the covariate) [32]. We used an α value of 0.05 for our significance threshold for all tests, and then applied a Holm-Bonferroni correction for tests with multiple comparisons on the same topic [16]. To apply this correction, we compare the largest p-value to 0.05, then compare the second largest p-value to 0.025, and continue as necessary [16]. The α values after applying the correction for up to four tests are: 0.05, 0.025, 0.0167, and 0.0125.

4 RESULTS

The tables displayed in this section include the mean, standard deviation, F-statistic, p-value, and partial eta-squared effect size [32] of the ANCOVA tests we conducted. Table 2 shows the comparison between lecture attendance, programming assignments (PAs), exams, and course grades that students earned. Table 3 shows the comparison of the survey items related to peer support, competitiveness, and sense of belonging.

4.1 Lecture Attendance

The results of the ANCOVA analysis in Table 2 shows that, after accounting for students' year in university, there is a statistically significant difference in attendance rates. The students in the blended learning group, on average, attended 82.65% of lectures—5.5 percentage points greater than the in-person learning group. In terms of a 20-lecture course, this translates to roughly a one lecture difference in total attendance between learning groups.

Table 2: ANCOVA test of student grades between in-person (n = 232) and blended (n = 241) learning group [1]. A * indicates statistical significance.

Item	Pop	Mean	Std. Dev.	F-stat	p value	Eff. size
Attendance	Blended In-Person	82.65 77.16	19.47 21.49	13.03	0.003*	0.027
PAs	Blended In-Person	83.48 87.72	20.17 17.11	3.37	0.067	0.007
Midterm Exam	Blended In-Person	86.02 90.86	20.20 16.67	6.15	0.013*	0.012
Final Exam	Blended In-Person	74.76 81.44	26.56 22.96	6.82	0.009*	0.014
Course Grade	Blended In-Person	83.93 87.88	18.97 17.01	2.91	0.089	0.006

4.2 Student Grades

After applying a Holm-Bonferroni correction to the α values, our results show that students taught in the in-person lectures performed significantly better on the midterm and final exams. We also note that the in-person group earned course grades that were 4 percentage points greater, on average, than the blended group, though this difference was not statistically significant. Figure 1 shows the breakdown of final exam scores between students of each academic year (first-year, second-year, etc). The graph demonstrates a larger difference between first-years in the two learning groups, with a smaller difference present between second-years, and ultimately trivial differences between third- and fourth-year students. While only the final exam grades are depicted, this general trend of a greater difference between first- and second-year students was present in the midterm exam, PA grades, and overall course grades.

4.3 Peer Support

There was one question on the surveys regarding peer support (PS1). Though we did not observe a statistically significant difference according to our ANCOVA test, Table 3 shows that students in the in-person group had an average of 2.63 peers to reach out to, which was over 20% more peer connections in the course than the students who attended remote lectures.

4.4 Classroom Competitiveness

There were two questions on the surveys regarding classroom competitiveness (CC1-CC2). The responses show a significantly higher rate of feelings of classroom competition in the in-person learning group. Following the same trend as student grades and peer support, first- and second-year students had a larger disparity in feelings of classroom competition than third- and fourth-year students, as depicted in Figure 2.

[1]The sample size for student grades data is higher than the sample size for other analyses because student grades and attendance data is covered by a separate human subjects protocol that requires students to opt out of sharing data.

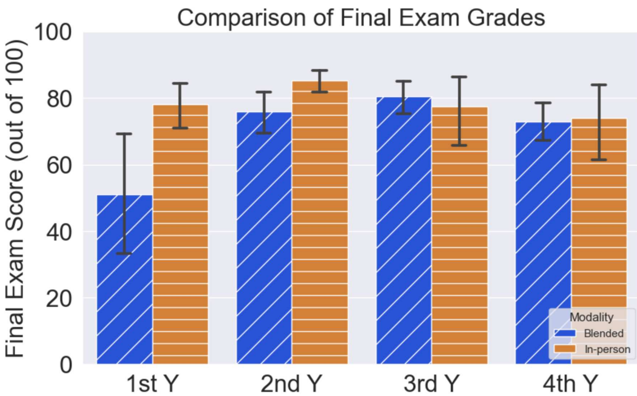

Figure 1: Comparison of average scores on the final exam among first, second, third, and fourth year students.

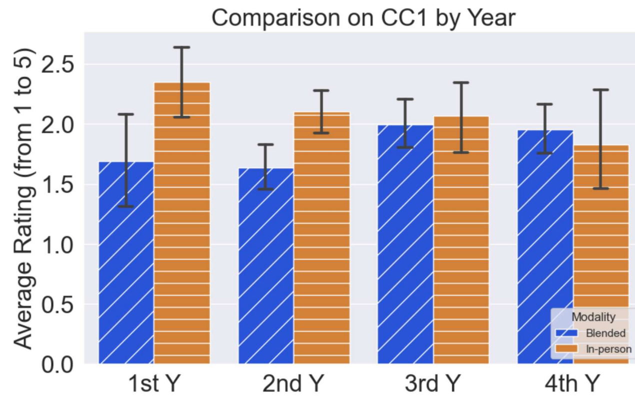

Figure 2: Comparison of responses on the item "CC1: I feel I am competing with other students in this class." A higher value indicates greater agreement.

Table 3: Comparison between in-person (n = 181) and blended (n = 198) learning groups on survey items about peer support, classroom competition, and sense of belonging. A * indicates statistical significance.

Item	Pop	Mean	Std. Dev.	F-stat	p value	Eff. size
PS1	Blended In-Person	2.06 2.63	1.86 1.80	2.68	0.102	0.007
CC1	Blended In-Person	1.86 2.14	0.86 0.98	12.52	<0.001*	0.032
CC2	Blended In-Person	1.78 2.14	0.81 1.04	9.09	0.003*	0.023
SB1	Blended In-Person	3.98 3.95	0.79 0.78	1.60	0.206	0.004
SB2	Blended In-Person	3.84 3.84	0.84 0.82	0.41	0.520	0.001
SB3	Blended In-Person	3.97 3.92	0.77 0.77	0.59	0.441	0.001
SB4	Blended In-Person	2.04 1.99	0.85 0.97	0.66	0.417	0.001

4.5 Sense of Belonging

On all four survey items related to sense of belonging (SB1-SB4), the p-values were above our α threshold and the effect sizes were minimal. Therefore, we detected no significant difference in sense of belonging between the two learning groups and did not observe a pronounced difference between first- or second-year students.

5 DISCUSSION

5.1 Key Findings

Our statistically significant results showed that students in the blended learning group:

- Attended more lectures throughout the term.
- Earned lower scores on the midterm and final exam.
- Reported having less feelings of classroom competition.

The higher attendance in the blended learning group is encouraging, as a known difficulty in teaching a virtual class is the lower attendance during lectures [17]. However, a surprising finding in combination with the higher attendance by the blended learning group is that this same group performed markedly *worse* on assignments and exams. We present two interpretations to help explain this relationship. First, a higher lecture attendance does not necessarily indicate greater lecture engagement. Therefore, just because more blended learning students were *present* at lectures, they may not have learned as much as the in-person students, who perhaps were more attentive during lectures. Second, it may be the case that lectures have an ultimately minimal impact on students' exam grades, as there are numerous other experiences such as programming assignments, textbook readings, labs, discussion, etc. that can impact a students' learning.

Another interesting correlation we found is that the learning group with more feelings of competition—the in-person group—performed *better* on exams and assignments. It may be the case that some students in an in-person lecture experience competitiveness because they *see* other students, perhaps sitting in the front of the class, raising their hands and seemingly knowing the answers to the questions that the instructor poses. Indeed, a "defensive climate", which Barker et al. first discussed, may have been formed in the in-person lectures in which students created an informal hierarchy based on these communication patterns [4]. In an in-person lecture, where all the other students are *physically visible* to all other students, students may have also felt greater pressure of competition simply from observing other students nodding along during lecture or seeming to understand the material. In contrast, students in the Zoom lectures asked questions via chat and there was no concept of the front or back of a class. Since most of the class turned their camera off, revealing only their names, there were limited physical cues to contribute to the "defensive climate."

Despite the in-person lecture students having more feelings of competition, they performed better on exams and assignments, leading to a roughly 4 percentage point difference in overall grades (Table 2). In terms of learning outcomes, our results are in contrast to the very similar work conducted by Gulati et al. [14]. In their work, they found that there was no difference in the two groups' exam scores and concluded that online lecture sections were an effective way to manage larger class sizes without impacting learning outcomes [14]. Our results do not paint the same picture, as the blended learning group consistently performed worse on assignments and exams. On the other hand, our findings do align with Gulati et al. regarding sense of belonging [14]. Despite the notion that remote lectures are potentially more isolating, this seemingly did not have a major impact on whether students felt accepted, supported, and comfortable in the course. A potential explanation of the lack of significance in our results is that practices such as peer instruction and pair programming on weekly assignments mitigated the isolating virtual lecture experience. However, we note that students did attend in-person labs and discussion sections, providing opportunities to interact with peers and make connections. A second potential explanation of the lack of significance is that the students in both groups were primarily non-CS majors, which may have also impacted students' belonging in the course.

Finally, a consistent trend in our results was that first-year students experienced the largest impacts among their learning group, though we could not conduct statistical tests for these sub-comparisons due to small sample sizes. Nonetheless, Figures 1 and 2, which demonstrate the trend that we saw across all student grades, peer support (not depicted in a figure), and classroom competitiveness, show that the largest disparities between modalities was seen among first-year students. A smaller, yet consistent, difference was present among second-year students in the two modalities, but third- and fourth-years showed inconsistent and trivial differences across course grades and all survey responses. It may be the case that first- and second-year students simply had less time to adjust to college coursework in a blended-learning setting, causing them to be less effective at learning in such an environment. The first-year students in the in-person lecture also seemed to perceive a higher level of classroom competition than those in the remote lecture. These younger students could be more prone to perceiving the "defensive climate."

5.2 Threats to Validity

First, a key confounding variable was that the in-person learning group had a different instructor than the blended learning group. However, we took steps to mitigate this concern. The instructor for the in-person group often observed the lectures by the instructor of the blended group and emulated the blended instructor's teaching practices. Further, all course content and course policies, including grading and assessments, were identical between the two groups. Finally, the instructor of the blended learning group (which performed worse on exams and assignments) was an experienced instructor who had taught the course for four years. On the other hand, the instructor of the in-person group was a first-time instructor that had not taught this specific course before. Further, we analyzed students' evaluations for the two instructors, though we caution that these evaluations suffer from gender biases [20]. The instructor of the remote sections received a 95.1% recommendation rate from their students, whereas the instructor of the in-person sections received an 85.3% recommendation rate. Therefore, we expected the impact of the instructor to be the *opposite* of what was observed based on our instructors' experience and comfort level in the course. Nonetheless, it may certainly be the case that some of the differences detected are due to differences among instructors.

Second, our population is limited to CS1 students, typically with limited prior coding experience. Further, the majority of our students were non-computing majors. Therefore, we caution against generalizing the results of this study to other CS courses, since novice programmers not intending to major in computer science may have different learning goals and needs.

Third, we did not use validated or previously-published survey questions for our peer support and classroom competitiveness analysis because we could not find suitable questions for these two topics. Though we crafted the questions to be clearly understood by students, there may have been issues with the wording of the questions and confounding effects that impact students' responses to these questions.

Finally, we note that researchers have cautioned against a misinterpretation of the ANCOVA statistical test due in the presence of multiple confounds between groups [30]. In our case, we certainly acknowledge that the selection bias between the groups extends beyond the students' year in the program. For example, perhaps the students that selected the in-person lecture were more motivated and passionate about computing, resulting in differences between the lecture sections. Therefore, we caution readers that there may be confounds that are unaccounted for using our ANCOVA analysis. Though we do not report on the effects of prior experience, we ran our ANCOVA analyses with prior experience as a covariate and still found the same significant results.

6 CONCLUSION

Our work provides insight to the nuanced differences in experiences between a fully in-person learning group and a blended learning group. Students in the in-person learning group fared better academically, with better outcomes across exams and a slightly higher course grade. However, the in-person group also experienced more feelings of competitiveness, likely due to the nature of communication in the traditional classroom setting. Notably, both groups of students had a similar number of peers to reach out to and a similar sense of belonging in the course. Readers should note, however, that our findings do not answer the question of which modality is better for students overall. Instead, given the conflicting results of previous works, our findings should serve as a single data point within the larger body of work surrounding the impacts of blended learning. Our work should inform instructors of CS1 courses about some of the potential advantages and drawbacks that students may experience in a blended learning course.

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