Who Uses Office Hours? A Comparison of In-Person and Virtual Office Hours Utilization

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ABSTRACT

In Computer Science (CS) education, instructors use office hours for one-on-one help-seeking. Prior work has shown that traditional in-person office hours may be underutilized. In response many instructors are adding or transitioning to virtual office hours. Our research focuses on comparing in-person and online office hours to investigate differences between performance, interaction time, and the characteristics of the students who utilize in-person and virtual office hours. We analyze a rich dataset covering two semesters of a CS2 course which used in-person office hours in Fall 2019 and virtual office hours in Fall 2020. Our data covers students' use of office hours, the nature of their questions, and the time spent receiving help as well as demographic and attitude data. Our results show no relationship between student's attendance in office hours and class performance. However we found that female students attended office hours more frequently, as did students with a fixed mindset in computing, and those with weaker skills in transferring theory to practice. We also found that students with low confidence in or low enjoyment toward CS were more active in virtual office hours. Finally, we observed a significant correlation between students attending virtual office hours and an increased interest in CS study; while students attending in-person office hours tend to show an increase in their growth mindset.

CCS CONCEPTS

• **Applied computing** → *Interactive learning environments*; • **Social and professional topics** → *Computer science education*; *User characteristics.*

KEYWORDS

Office Hours, Computer Science education, Data Analysis, Correlation Analysis

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1 INTRODUCTION

Enrollment of CS courses has increased substantially over the past decade creating a greater demand for support through office hours. While most instructors have increased office hours as their classes have grown, prior research has indicated that traditional in-person office hours have been underutilized by students [17]. Consequently some instructors have moved office hours online to better support students. [10] This shift has accelerated in 2020, due to the pandemic. As courses are returning to in-person interaction, instructors are weighing whether office hours should change back to in-person, stay online, or use some combination of the two modes. Our goal in this research is *to assess the relative uptake of online office hours and to understand the impact of the format on students' use of office hours, their attitudes toward the course, and their learning.*

We address the following research questions:

- RQ1: Do students utilize office hours differently, or face differing wait and interaction times, when participating in office hours in-person and virtually?
- RQ2: Do students perform differently in a course when using in-person or virtual office hours?
- RQ3: Does the use of virtual office hours change the demographics or characteristics of students who attend them?
- RQ4: Does the format of the office hours affect students attitudes about CS problem solving?

To address these questions we compared the performance of students in a CS2 course across two semesters, Fall 2019 and Fall 2020. Students in Fall 2019 used in-person office hours while Fall 2020 featured all virtual office hours. Both groups were part of the same program and had similar overall demographics and course structure. For RQ1, we extracted wait times, interaction times, and other data about office hours from My Digital Hand, our office hours management tool, to compare the interactions across the groups. For RQ2, we compared the performance of students who attended office hours between the delivery modes and for RQ3 we combined the office hours interaction data with demographic or attitude information to characterize the students who utilize each mode of office hours. For RQ4 we examined students' self-reported attitudinal information through a pre- and post-class surveys to assess the change across the courses.

2 BACKGROUND

The under-utilization of in-person office hours is a concern of many instructors and researchers. Smith et al. [17] investigated low office hours utilization by designing a survey asking students' and instructors' view on office hours. They found that many students were unclear on how, when, and why to use the office hours. Some students suggest they only go to the office hours when they are "doing a very very bad job at the course". The authors suggest that instructors could apply a digital tool to support office hours and frequently promote attending office hours to students. Ryan and Pintrich [15] also showed that avoidance of help seeking might be indirectly affected by student's social competence. MacWilliam and Malan [9] saw increased attendance by moving office hours to a more social location. This motivated our focus on the relationship between individual characteristics and office hour format.

Several experiments of hosting virtual office hours have been done. Malan [10] introduced virtual office hours into Harvard's introductory CS course and expected to see a boost in the participation. However, they found that the attendance to virtual office hours was similar to in-person attendance [10]. Gao et al. [6] observed a significant boost of attendance in virtual office hours of a CS2 course. Li and Pitts [8] conducted a survey to ask student's opinion of their experience with in-person and virtual office hours. The results show that students are more satisfied with the virtual option, but that both options of office hours are actually underutilized. The authors suggest that the low attendance might be due to the low course enrollment. There are no clear results that virtual office hours increase participation; increased utilization may be dependent on course context.

Morgan and Robinson [11], by contrast, did find that there are significant difference of students help-seeking behavior by different gender, ethnic background, and status. Ames and Lau [3] showed that students with previous poor performance are more likely to seek help. We investigate student performance, demographics, and academic attitudes with office hours interaction mode.

3 DATA COLLECTION

We collected our data from the second course (CS2) of a three-semester introductory sequence for computer science majors and minors at a research-intensive public university in the United States. The CS2 course covers advanced object-oriented programming, software engineering skills, linear data structures, finite state machines, and recursion. The Fall 2019 (F19) offering of CS2 was held in-person with face-to-face office hours while the Fall 2020 (F20) offering was conducted online due to the COVID-19 pandemic. Apart from the change in instructional mode the only other change was the use of weekly quizzes in F20 in lieu of three exams. Assignments and labs, which are most frequently discussed in office hours, were of similar structure, making the two semesters an ideal point for comparison.

Students completed a pre-survey during the second week of the class and a post-survey during the last week of class. These surveys are discussed in Section 3.1. We used the second week of class for our pre-survey due to fluctuations in the course role during the first week. Consistent with our IRB we excluded students who did not consent to participate in our study and who were under 18. As shown in Table 1, in F19, we received 105 pre-survey and 86 post-survey responses. In F20, we received 105 pre-survey responses and 75 post-survey responses. For each consenting student who completed the survey we also collected data on their use of office hours through our ticketing system My Digital Hand (MDH) [16].

Table 1: Course information for two semesters studied

	F19	**F20**
Course Operation	in-person	virtual
Total Enrollment	256	303
Consenting students	110	118
Valid Pre-survey Response	105	105
Valid Post-survey Response	86	75

3.1 Survey

The pre- and post-surveys contained four common sections; the pre-survey also contained a section collecting demographic information. Our focus is on the *attitudes* and *background* information[1].

The *attitudes* portion of the survey utilized the full Computing Attitude Survey v4 (CAS) [5], which measures problem solving – transfer, personal interest, problem solving – strategies, real-world connections, and problem solving – fixed mindset. We also included two factors from the Computer Science Attitudes (CSA) survey [19] on confidence and effective motivation. The CSA survey included questions in both factors in the positive and negative direction and we utilized only the positive questions to better mirror most of the CAS questions and to minimize survey fatigue [12]. Both the CAS and CSA use five-point Likert scales from "Strongly disagree" to "Strongly agree". To simplify analysis, we combined "Strongly disagree" and "Disagree" into a "Disagree" category with a similar transformation into an "Agree" bucket. We could then compare the students' responses in each of the categories of questions with an expert's expected attitude. For example, for the category of "Personal interest", we would expect that an expert computer scientist would "Agree" with all the statements.

- **Problem Solving - Transfer** (CAS v4 [5]): measure the student's attitudes on transferring concepts to practice. Expert opinion – Disagree.
- **Personal Interest** (CAS v4 [5]): measure the students' interest in CS study. Expert opinion – Agree.
- **Problem Solving - Strategies** (CAS v4 [5]): measure the students' coding habits or strategies for solving CS problems. Expert opinion – Agree.
- **Real-world Connections** (CAS v4 [5]): measure the students' belief they can apply CS skills to other areas. Expert opinion – Agree.
- **Problem Solving - Fixed Mindset** (CAS v4 [5]): measure the students' mindset toward solving CS problems. Expert opinion – Disagree.
- **Confidence** (CSA [19]): measure the students' confidence with problem solving. Expert opinion – Agree.
- **Effective Motivation** (CSA [19]): measure the students' motivation to solve CS problems independently. Expert opinion – Agree.

The *background* section of the survey asked students to provide demographic information and included questions about their prior experience, if the student is attempting the course for the first time, age, gender, race/ethnicity, and class standing (e.g., freshman, etc.). The last four questions were all optional.

[1]The full surveys will be provided via a supplemental website after acceptance.

3.2 Office Hours Interactions

Students attended a majority of office hours in-person during the Fall 2019 semester[2] Students in Fall 2020 attended office hours online via Zoom. In both semesters, we used My Digital Hand (MDH) [16] for managing the office hours queue. Students create a ticket in MDH to "raise" their hand for help. For in-person office hours, students would submit their ticket when they arrive to the office hours room. For virtual office hours, students would submit their ticket once the teaching staff member has started their help-session. The ticket includes information about the assignment they are working on, their problem, and a link to their GitHub repository. When a member of the teaching staff is ready to help the student, they notify the student and start the interaction in MDH. Once the interaction is complete, the teaching staff member closes the interaction. The MDH system will automatically record the start time, end time, and participants for each interaction.

One challenge is that the interaction relies on the teaching staff member opening and closing the interaction. In practice, there are times where the interaction is opened several minutes into a meeting with a student (or even after the meeting is complete). Additionally, teaching staff may forget to close interactions when their office hours are over. To address this problem, we drop all the interaction records of less than 1 minute and longer than 60 minutes when analyzing the correlation of the long interaction in RQ3. We keep those interactions when analyzing attendance because they represent actual interactions.

4 METHODS

Our research focuses on investigating the relationship between the student's office hours interaction behaviors for in-person or virtual office hours. By characterizing the types of students who attend in-person or virtual office hours, we can make more informed decisions about future allocations of teaching staff to office hour mode. Therefore, we calculated several correlations to answer our research questions. A summary of our analysis is in Table 2. We use Pearson's correlation coefficient [7] when both variables are continuous and we apply the Kruskal-Walis test when one of the variable is un-ordered categorical data [1].

4.1 RQ1: Interactions

RQ1: Do students utilize office hours differently, or face differing wait and interaction times, when participating in office hours in-person and virtually?

In RQ1, we compare the utilization, interaction, and wait times between in-person and virtual office hours. Our goal is to understand how the student experience is impacted when considering mode of office hours interaction. For example, Smith et al. [16] found that office hours utilization ranged from 36% of students to 79% of students across three institutions over two semesters of study. Additionally, students can wait on average fifteen minutes to an hour to receive help from a member of the teaching staff [16]. Interaction times ranged from 17 to 32 minutes [16]. Ren et al. [13] found that 90% of students in the CS1 course they studied attended office hours. Office hours utilization, wait times, and interaction times can vary by semester and institution, but differences between in-person and virtual have not yet been studied to our knowledge.

4.2 RQ2: Performance

RQ2: Do students perform differently in a course when using in-person or virtual office hours?

To answer RQ2, we analyzed the correlation between students' performance and their use of office hours. Their performance was represented by the final grade of each student and the office hours attendance is measured by the total count of MDH interactions for each student. This correlation helps us to understand the relationship between office hours attendance and student grades; a positive correlation would suggest that students who attend office hours more often receive higher grades in the course. By comparing F19 in-person office hours attendance and F20 virtual office hours attendance, we could identify if one mode of office hours might be preferable to support student success.

4.3 RQ3: Student Characteristics

RQ3: Does the use of virtual office hours change the demographics or characteristics of students who attend them?

To represent the student's *attitudes*, we used the factors from the CAS v4 and CSA as described in Section 3.1. For each factor or category, we merge the "Strongly disagree" with "Disagree" and merge "Strongly agree" with "Agree". Then, if the student's response would match the expert attitude, we add one to the category (all categories start with a score of 0) and if the response is the opposite of the expert's expected attitude, we subtract one from the corresponding category. Each *attitude category score* represents the student's overall attitude in that category. Since the expert opinion are treated as a mature and positive opinion, a larger category score usually indicates that the student has a more mature view of learning CS. For example, if a student disagreed with all four questions of the *Problem Solving - Transfer* category, matching the expert attitude of "Disagree", their score would be four. A score of zero means that the student is mixed in their attitudes about a category. A negative score means that the student is demonstrating characteristics opposite of what we would expect from a CS expert. Therefore, a negative correlation between the "Transfer" attitude score and office hours attendance would indicate that students with *weaker* transfer skills would have more office hours interactions. Similarly, a negative correlation with the "Fixed Mindset" attitude score would indicate that students with *more* fixed mindsets would have more of the correlated variable.

We gathered the students' *background* information about their prior experience, course attempt status, age, gender, race/ethnicity, and class standing. The questions were all categorical data except for age. Therefore, when we test the correlations with these variables, we use the Kruskal-Wallis test.

We then evaluate the correlation between *attitudes* and *background* in the pre-survey and 1) office hours attendance, and 2) the percentage of their interactions that are considered long (over

[2] One section of the course is offered online asynchronous for continuing education students working on a certificate. We offered two hours of online office hours per week for distance education students. On-campus students could attend those office hours, but priority was given to students in the distance education section. They are considered in the analysis.

Table 2: Correlation Analysis Overview

Analysis	RQ	Variable 1	Variable 2	Test Applied
1	RQ2	Performance (Grades)	Office Hours Attendance	Pearson's Correlation Coefficient
2	RQ3	Attitude Categories	Office Hours Attendance	Pearson's Correlation Coefficient
3	RQ3	Background Information	Office Hours Attendance	Kruskal-Wallis
4	RQ3	Attitude Categories	Percentage of Long Interaction	Pearson's Correlation Coefficient
5	RQ3	Background Information	Percentage of Long Interaction	Kruskal-Wallis
6	RQ4	Attitude Category Change	Office Hours Attendance	Pearson's Correlation Coefficient

10 minutes). We defined *long interactions* as interactions that last over 10 minutes. Ten minutes was the suggested interaction time in Smith et al. [16], the default interaction time in the MDH interaction timer, and was around the median duration of office hours interaction for both semesters after dropping the interactions less than one minute.

4.4 RQ4: Student Change

RQ4: Does the format of the office hours affect students attitudes about CS problem solving?

For RQ4, we calculated the correlation of office hours attendance with the change between the students' pre- and post-surveys on the *attitude* categories. We first convert student's *attitudes* to a score as described in Section 4.3. We take the difference between the post-survey score and the pre-survey score to represent the attitude shift for each survey question. Then, we sum the shift across statements within the same category to get the *attitude category change score*.

By examining the *attitude category change score*, we can measure the students' growth (or decline) in the course. For instance, if a student has a change score of 12 in the "Confidence" category, it means that they changed from low confidence about solving computer science problems to high confidence in solving CS problems. An increase in confidence, or maintaining a high level of confidence, over the course of a semester suggests that students are prepared for academic success in future CS study [4]. And by analyzing the correlation between personal growth and office hours attendance we can identify if there is a possible relationship between attending office hours and a student's personal growth. Any differences between the correlations with in-person and virtual office hours, can suggest how to structure office hours in future course offerings.

4.5 Bonferroni Correlation Correction

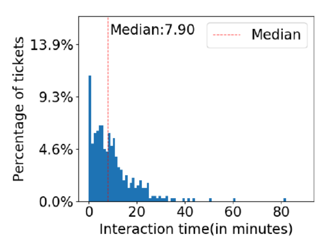
Each set of correlation calculations considers multiple correlation tests. However, when testing multiple statistical null hypotheses during the correlation calculation the chance of observing a rare event increases and it might increase the likelihood of rejecting the null hypothesis and the resulting p-value is actually amplified. Therefore, we apply the Bonferroni correction to adjust our p-value. [18] The Bonferroni correction changes the confidence level from α to α/n, where n represents the number of tests. We adjusted the p-value by multiplying it by the number of correlation tests in a given set. After the adjustment, if the p-value is less than 0.05, we believe it suggests a significant correlation. [2, 14]

5 RESULTS

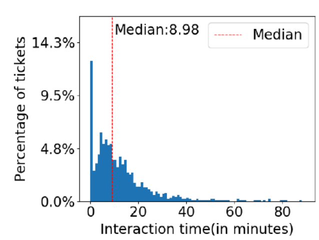
5.1 RQ1: Analysis of Interactions

We found that only 58% of students in F19 attended office hours at least once, while in F20 this number increased to 70%. Also the average number of office hours attendance is 3.90 in F19 and 13.60 in F20. The difference in office hours attendance between the two semesters is significant ($p = 0.0004$) using the Kruskal-Wallis test. Virtual office hours, in our course context, were more highly utilized that in-person office hours.

Figure 1 shows the interaction times in F19 and F20. We found the median interaction time in F20 (8.08 minutes) is slightly longer than in F19 (7.9 minutes). Also, a larger percentage of interactions were less than one minute in F20 (14% VS 11% in F19), which suggests that the teaching staff might have made more mistakes when recording the interaction time in F20, possibly due to managing several online tools at once. After we drop all the interactions less than one minute, the median value of interaction time is 9.36 minutes in F19 and 11.74 minutes in F20. The longer interaction times in F20 indicates that virtual office hours might be more time consuming. The additional time may be due to connection delays and screen sharing delays. However, the differences are only a few minutes and may be negligible when considering other differences in who attends office hours.



(a)

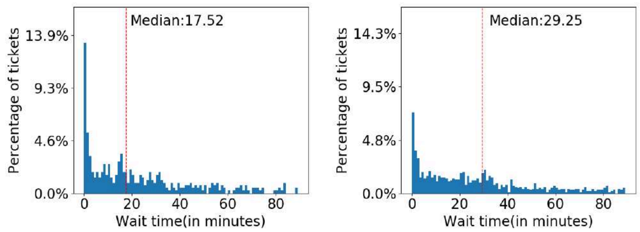


(b)

Figure 1: Interaction Times for (a) F19 and (b) F20

Figure 2 shows that the median wait time is 17.52 minutes in F19 and 29.25 minutes in F20. A Kruskal-Wallis test showed that the difference between the semesters with wait time is significant ($p = 0.0002$). This significant gap shows that students waited almost twice as long in F20 to get help. The long wait time is likely due more to the long queue through higher utilization rather than increase interaction time.

These results indicate that online office hours were more heavily utilized than in-person office hours for the CS2 course. However, there was a slight increase in interaction time and a large increase



(a) (b)

Figure 2: Wait Times for (a) F19 and (b) F20

in wait time. Since the goal is to promote student help seeking, these results indicate that continuing with some online office hours would be beneficial to promote and expand access while setting expectations to streamline efficiencies.

5.2 RQ2: Analysis of Performance

We found no significant difference in grades between the two semesters through a Kruskal-Wailis test ($p = 0.325$). The median grade in F19 is 90 while in F20 is 91; about half of the students achieved an excellent grade in both semesters. A similar percentage of students earned less than a 70 in both semesters (10.5% in F19 and 12.7% in F20). In the CS2 course context, mode of office hours appears to have no relationship with course performance.

Additionally, when considering Analysis Set 1, we found no significant correlation between the student's office hours attendance and final grade in both F19 and F20. For F19, the p-value was 0.827 ($r = 0.081$), while for F20, the p-value was 0.726 ($r = 0.090$). This suggests that office hours attendance is not related to student grades in CS2.

5.3 RQ3: Analysis of Student Characteristics

Table 3: Correlation between office hours attendance and 7 Attitude category score

	F19		F20	
	r	Adjusted p	r	Adjusted p
Transfer	-0.271	0.035	-0.247	0.077
Personal Interest	-0.105	>0.1	-0.363	0.001
Strategies	0.064	>0.1	0.19	>0.1
Real-world	-0.143	>0.1	-0.024	>0.1
Fixed-mindset	-0.337	0.002	-0.341	0.002
Confidence	-0.145	>0.1	-0.315	0.007
Effective motivation	-0.054	>0.1	-0.016	>0.1

Table 3 shows the correlations for Analysis Set 2, which explores the relationships between *attitudes* and office hours interactions. We see significant relationships in F19 and S20 for "Fixed Mindset". Because the "Fixed Mindset" statements had a "Disagree" expert opinion, we interpret the results as a weak to moderate negative linear relationship, which suggests that students with fixed mindsets attend office hours more frequently. There is also a significant, weak to moderate negative linear relationship in F19 for the "Transfer" category. Similar to "Fixed Mindset", with an expert option of "Disagree," this indicates that students struggling with transferring concepts to practice attend office hours more frequently.

In F20, there are other *attitude* categories that have significant relationships: "Personal Interest" and "Confidence". Both of these *attitude* categories have the "Agree" expert opinion, which means that the weak to moderate negative correlation shows that more students who disagreed with the statements in these *attitude* categories attend office hours. This is encouraging that students who know that they need help are more likely to attend office hours. The results suggest that virtual office hours may better support struggling students with fixed mindset, lower personal interest in CS, and lower confidence.

For Analysis Set 3, which explores the relationships between the *background* information and office hours interactions, we found gender has a strong correlation with the office hours attendance in both semesters. In F19, the adjusted p-value was 0.045 (H=6.234); while in F20, the adjusted p-value was 0.027 (H=7.757). The other *background* items have no correlation with office hours attendance. Our finding shows that women tend to attend office hours more frequently both for in-person and virtual office hours.

Analysis Set 4 aims to discover any relationship between student *attitudes* and the percentage of their office hours interactions that were *long interactions* (e.g., over 10 minutes). In F19, all *attitudes* categories have no linear correlation with the student's percentage of long interactions (all adjusted p-value >0.1). In F20, only the "Strategies" category has a significant correlation (adjusted p-value = 0.007). Since the correlation is positive, this suggests that students with a stronger belief in their problem solving strategies asked more *long questions* during office hours in F20. This could suggest that virtual office hours may support asking more complex questions. One possibility is that the other students waiting are less visible so there may be less pressure to keep questions short in a long queue. Another possibility is that the wait times (as discussed in Section 4.2) encouraged students to ask lots of questions during their interaction to avoid getting back on the queue.

The correlation results for Analysis Sets 5 showed p-values greater than 0.1 (all $H < 4.5$). Thus we did not observe a statistically significant linear relationship between the student's *background* information and the percentage of long interaction for office hours.

5.4 RQ4: Analysis of Student Change

Our last research question considers the change in student *attitudes* between the pre- and post-surveys and their office hours attendance. Table 4 shows the average attitudes category scores for pre-survey and post-survey, and the difference between them in F19 and F20. We observe that except for "Effective motivation", F20 has a larger increase in each attitude category, which suggests that students saw positive attitude changes in CS during the online semester.

In Analysis Set 6, we found that the *attitude category change score* in "Fixed Mindset" shows a significant weak to moderate positive correlation ($r = 0.371$, adjusted p-value=0.007) with office hours attendance in F19, meaning student who attend office hours more frequently in F19 improved their computing mindset. Also, in F20, the category change score for "Personal Interest" shows a significant weak to moderate positive correlation ($r = 0.326$, adjusted

Table 4: Average pre and post category scores in F19 and F20

	F19			F20		
	pre	post	diff	pre	post	diff
Transfer	2.76	2.79	+0.03	1.92	2.36	+0.44
Personal Interest	3.58	3.46	-0.08	3.37	3.70	+0.33
Strategies	4.08	4.15	+0.07	4.06	4.48	+0.42
Real-world	2.31	2.52	+0.21	2.46	2.73	+0.27
Fixed-mindset	6.34	6.45	+0.21	5.54	6.14	+0.6
Confidence	4.71	4.76	+0.05	3.78	4.65	+0.87
Effective motivation	4.71	4.56	-0.15	4.93	4.87	-0.06

p-value=0.017). Therefore, students who attend office hours more frequently in F20 appear to see an increase in CS interest.

6 LIMITATIONS

When measuring office hours interaction time, we rely on the accuracy of the data collected by MDH. The main inconsistencies in the interaction time data are from the teaching staff forgetting to start an interaction after connecting with the student and from forgetting to close an interaction after finishing with a student. We handled this by dropping all the interaction less than one minute and longer than 60 minutes when analyzing the correlation of long interaction in RQ3. There may be a few office hours interactions by consenting students that were not collected, especially at the start of the semester as we onboarded students to MDH or if the MDH system went down.

Another limitation we are facing is that our analysis considers two semesters of a single course. Results may be different for another course or another semester, as seen with mixed utilization data in the related work. Additional analysis of future semesters and other courses would provide additional understanding to office hours interactions and if utilization and other attendance characteristics are dependent on classroom and instructor context. This is especially important for evaluating virtual office in a non-pandemic situation.

Moreover, since most of our entire analysis involved correlation tests, we cannot make any conclusions about causation. What we can do is to test and support our findings by different approaches. For instance, in the future, we could conduct another survey directly asking student's opinion on office hours usage, their reasons for attending office hours or not, and preferences on different office hours mode.

Also, we compared the difference of two office hours mode by comparing data patterns in F19 and F20. However, the shift in office hours is not the only difference between F19 and F20. In F20, all the lectures and labs were also held online and the insructors witnessed an unusually high percentage of academic difficulties. Therefore, there may be other factors that explain the change and further study including within-semester comparisons would be informative.

7 CONCLUSIONS & FUTURE WORK

We found a significant increase in office hours utilization when offered virtually. However, virtual office hours had longer interactions and wait times, likely due to the increased utilization. Virtual office hours may increase access, which along with connection challenges, could impact interaction and wait times. Also, both semester's average interaction time is shorter than the range suggested by Smith et al. [16]. And both semesters also have a lower percentage of students participating than the 90% in Ren et al. [13]'s research. This may suggest that institutional context and class culture impacts office hours help seeking.

Our findings in RQ2 show that both in-person and virtual office hours are attended by students with varying success in the course. In general, there is no clear relationship between attending office hours more often and better grades for one-on-one help-seeking. Students who do not attend office hours can do well in the course because they may be able to complete activities without additional help or seek help asynchronously via the course forum.

In RQ3, our results suggest students with a fixed mindset in CS and women utilize office hours more frequently, no matter the mode of office hours interaction. Moreover, for virtual office hours, students with low-confidence and low-enjoyment toward solving CS problem, are more likely to participate . We think this might be because virtual office hours provide students a sense of security and feel less embarrassed when asking simple questions. We also found that the students who have a better problem solving strategies are more likely to make long interaction rather than short regular interaction when the office hours are online. Our interpretation of this result is that this type of students usually are able to solve easy-to-answer problems by themselves, and when they do attend office hours, their problems are usually more challenging. Since this pattern only exists in F20, we believe that the popularity of the online office hours encourage strong skill and strategy students to focus their questions on high-impact discussions or to ask many questions in a single interaction due to wait times.

RQ4 looks at the relationship between office hours attendance and personal growth on CS *attitudes*. We found that attending virtual office hours is related to an increase in interest CS study; while attending in-person office hours is associated with an improvement of CS mindset.

All of these finding shows that the in-person and virtual modes of office hours have their own advantage and attract different types of students to participate. Therefore, we believe that instructors should consider providing both options for students to accommodate their preferences and efficiencies. Students with low confidence and low enjoyment toward CS problem solving benefit from a virtual option, and in-person office hours may minimize wait time.

In the future, we could investigate and measure the effectiveness of office hours by tracking student's action and status on auto grading systems after the office hours interaction finished. Those action and status could increase confidence that the office hours interaction lead to some type of forward progress on student assignments.

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