Evolution of female and minority engagement in teams as online meetings became the norm

We examine how students' engagement in project teams evolved as online meetings became the norm during the disruptive COVID-19 pandemic. We collected a comprehensive dataset of meetings, emails, and surveys from Spring 2020 to Spring 2021 across 18 student project teams in social science and STEM courses at a large public university. We use natural language processing and machine learning classification methods to process and analyze 88 online meetings. Our evidence suggests that females and minorities suffered more from online meetings. Females decreased total time spent speaking and giving information after online meetings became the norm. Asian and Hispanic students spoke significantly less frequently in online meetings at the beginning of the COVID-19 pandemic,. This gap remained but diminished after online meetings became the norm. There is no evidence that either total or average online meeting time changed before and after the normalization of online meetings.

CCS Concepts: **Applied computing** → Law, social and behavioral sciences; Education; **Human-centered computing** → Human computer interaction; Collaborative and social computing

KEYWORDS: online meetings, virtual meetings, video conference, natural language processing, student engagement, females, minorities, COVID

1 INTRODUCTION

Online meetings became essential during the COVID-19 pandemic and are likely to remain a common part of future interactions in cooperative work and learning environments. Hence, it is necessary to investigate how computer-assisted meeting modality affects participants' engagement, and researchers have mostly considered such a question via surveys (Alharbi et al., 2021; Kaptelinin et al., 2021; Karl et al., 2021; Bayhan et al., 2022; Standaert and Thunus, 2022). In this paper, we aim to answer three questions from a unique meetings dataset we collected from the emergence of the COVID-19 pandemic onwards. First, we ask whether online meeting format alters students' engagement patterns in project teams and whether this effect is heterogeneous by gender and race. Second, we analyze how individual and team performance changed as online meetings became the norm. Third, we examine if the dynamics of meetings over the course of the project changed.

Supported by part of a National Science Foundation Future of Work grant that aims to study and improve communication in smaller-size student and larger-size construction project teams, we collected meetings, email exchanges, and surveys of 18 undergraduate and graduate student project teams in social sciences and STEM from Spring 2020 to Spring 2021—covering the onset, peaks, and troughs of COVID-19. All courses required students to form teams to conduct group projects. The videos from team meetings were recorded, which allowed us to analyze student engagement. Throughout the semester, several waves of surveys were conducted to extract demographic information, along with individual and team performance.

We transformed raw video recordings for our qualitative and quantitative analysis via natural language processing and other machine learning methods. We diarized and transcribed our meetings via the Kaldi project, allowing us to summarize the total engagement time of individuals. We employed a supervised machine learning method to categorize each utterance of a speaker into either giving information or asking for information (or neither). We also conducted sentiment analysis of each utterance (outside scope of this paper).

We use the proportion of speaking duration (pdur) in a meeting for an individual as the basis of measures of individual engagement. Regression results suggest that the medium of communication has heterogeneous effects by gender and race. The online modality does not have a negative effect on engagement for male students. However, engagement from female students decreased after online meetings became the norm. A further test suggests that this decrease came mostly from "giving" less information, but not from "asking" fewer questions. This combination of results suggests that online meetings may have a larger adverse influence on women's engagement in tasks that involve group coordination.

We also find racial disparities in student engagement. In our data, engagement of Asian and Hispanic students was significantly lower than among White students in Spring 2020, the first semester of online teaching. However, the racial gap in engagement declined as online meetings became the norm, at least between Asian and White students. This implies that the online learning format has instant negative impact on engagement for minority students. But, growing familiarity with online learning gradually built up confidence for minority students and helped them to grow more comfortable in sharing ideas and asking questions, but the gap was not completely closed. Surveys conducted by Wu and Teets (2021) also reveal a decrease in student engagement, with underrepresented people of color reporting significantly greater decreases in three of the four engagement components: skills engagement, participation engagement, and performance engagement.

We also investigate peer evaluation of individuals in survey responses. We find that disruption due to COVID-19 lowered peer evaluation. There is no gender difference in average evaluation, but Asians on average lower ratings. Furthermore, we did not find statistical significance in changes in meeting lengths.

Our results accompany previous documentation of gendered and racial effects of COVID-19 on productivity and engagement (King and Frederickson, 2021; Wu and Teets, 2021; Standaert and Thunus, 2022; Staniscuaski et al., 2022), but differ in two significant ways. First, previous studies focus on academics or labor force measures. Such adverse effects could be driven by family considerations such as childcare, which are expected to disproportionately affect women. We find that even among college students, where childcare is typically not a primary concern, adverse impacts still occur disproportionately for women when group coordination occurs through an online medium. Second, methodologically, previous studies draw their conclusions from surveys or outputs (such as academic papers), but our conclusions are based on more direct observed behavior.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 presents the detailed analysis regarding engagement, performance, and meeting length, and Section 4 concludes.

2 DATA

2.1 Data Collection

We collected our data of meetings, emails, and surveys from a large Big Ten public university from Spring 2020 to Spring 2021. It includes Spring 2020, the semester that was disrupted by COVID-19, and subsequent three semesters (Summer 2020, Fall 2020, and Spring 2021) that were all or partially online. Table 1 summarizes course modalities across different semesters.

It covers a total of 18 student teams in 9 sections of 7 courses and 101 students. Table 2 summarizes which semester and course for each team functions, how many people are in each team, how many videos were recorded for each team, the average length of these videos, and the time frame of the project. A social science class can be in economics or human resources and labor relations class, a technical class can be a computer science or engineering class, and a hybrid class is in a field that consists of both social and technical components.

Table 1. University's course modality policies

Spring 2020: On March 11, 2020, MSU switched all classes from in-person to online meetings
Summer 2020: All classes were online
Fall 2020: All classes were online (announced right before the beginning of Fall semester)
Spring 2021: Most classes were online, with some in-person classes (not in our sample)

Table 2: Summary of project teams

Team	Semester	Course type	Team size	Number of videos	Average length (mins)	Date Range
A	2020spring	social	6	4	28	02/27/2020-04/24/2020
B	2020spring	social	6	2	57	02/21/2020-02/27/2020
C	2020spring	social	8	4	46	02/23/2020-04/27/2020
D	2020spring	social	8	6	26	02/21/2020-04/24/2020
F	2020spring	technical	9	3	39	04/09/2020-04/20/2020
H	2020summer	hybrid	5	5	46	07/14/2020-08/01/2020
I	2020fall	hybrid	4	13	43	10/02/2020-11/27/2020
J	2020fall	social	5	3	42	11/03/2020-11/19/2020
K	2020fall	social	5	7	53	10/30/2020-11/24/2020
L	2020fall	social	5	3	44	11/03/2020-11/17/2020
M	2020fall	social	5	5	26	10/21/2020-11/20/2020
N	2020fall	social	4	3	29	11/17/2020-11/29/2020
O	2020fall	social	4	3	12	11/18/2020-12/04/2020
P	2020fall	technical	6	7	17	11/06/2020-12/11/2020
Q	2020fall	technical	5	2	37	10/23/2020-11/17/2020
R	2020fall	technical	6	7	22	11/03/2020-12/02/2020
S	2021spring	social	5	8	22	03/04/2021-04/07/2021
T	2021spring	social	5	3	23	03/10/2021-03/29/2021

2.2 Data Processing via Machine Learning Pipeline

The raw dataset contains audio or video recordings of meetings, as well as eight surveys for every participant. We then build a natural language processing machine learning pipeline to process the raw audio and video. The pipeline starts from speaker diarization and speech recognition, followed by giving/asking/other information classification, and ends with sentiment analysis.

The speaker diarization module is aimed at splitting audio signals based on speaker identity. It first partitions the audio into small segments, each of which ideally contains a variable-length utterance from a unique speaker. Then, by comparing the audio signals in each segment, the module determines the number of speakers in a conversation, and judges which speaker each segment belongs to. We used Kaldi (2021) project to achieve this. In practice, we apply a deep learning speaker diarization model released in Kaldi speech recognition toolkit (Povey et al., 2011). The model first encodes utterances to fixed-dimensional embeddings which are called “x-vectors” (Snyder et al., 2018), and then performs agglomerative hierarchical clustering on x-vectors to produce an initial diarization output. Finally, a variational Bayes Hidden Markov model is applied over x-vectors to improve the diarization results. In our implementation, we use the pre-trained model from Kaldi Project (2021) and run it in ONNXRuntime (Povey, 2011).

The giving/asking/other information classification module is a text classifier that classifies utterances from speakers into three categories: giving information (G), asking information (A), and others (O). This module aims to determine whether an utterance is giving information to others, asking for information from others, or neither, to help us understand the information exchange in communications among team members. Subsequently we can focus on pertinent information exchanges in teams. We train a deep text classifier for this goal. Specifically, we build a 1-layer recurrent neural network (RNN) with gated recurrent units (GRU) as the text classification model. The size of word embeddings is set as 50 and the hidden size of the RNN is 128. The model is trained on 932 training instances manually labeled by human coders with a batch size of 64 for 20 epochs.

2.3 Control Variables

Many control variables are selected to control for demographic characteristics and course information. Familiarity indicates whether the individual is familiar with online learning format and is the dependent dummy variable. It equals 0 if the sample is from Spring 2020 and Summer 2020 semesters, and 1 otherwise. Female, Asian, Black, Hispanic, and White are all dummy variables representing gender and race. The number of team members is 5.81 on average. The average GPA in the sample is 3.59. The sample has a broad representation of both technical and social science courses, and 16% of the sample took a hybrid course (both technical and social science). The sample contains roughly equal amounts of undergraduate courses and graduate courses.

Table 3. Summary Statistics

variable name	mean	sd	min	max	count
familiarity	0.65	0.48	0	1	483
female	0.48	0.50	0	1	483
Asian	0.36	0.48	0	1	483
Black	0.04	0.18	0	1	483
Hispanic	0.05	0.22	0	1	483
White	0.55	0.50	0	1	483
team size	5.81	1.46	4	9	483
GPA	3.59	0.59	0	4	445
technical	0.41	0.49	0	1	483
social	0.75	0.43	0	1	483
hybrid	0.16	0.37	0	1	483
undergraduate	0.48	0.50	0	1	483

2.4 Engagement Measures

We use several metrics of speaking time duration to measure students' engagement. The first one is ***pdur***, which is the percent of speaking time duration (out of 100) in a meeting. Each student speaks 18.22% of total meeting time on average. To eliminate the effect of team size on pdur, two alternative engagement measures are generated.

The measure pdur1 is normalized measure by the entire sample, which transforms the distribution of pdur to resemble standard normal distribution.

$$pdur1 = \frac{pdur - mean(pdur)}{sd(pdur)},$$

The measure pdur2 takes into consideration that group size has inevitable influence on the value of percent duration. It thus subtracts the group mean from pdur and indicates the normalized standard deviation from the group mean.

$$pdur2 = \left(pdur - \frac{100}{size}\right) / sd(pdur\ within\ team\ within\ meeting).$$

Both measures have a normalized mean of zero.

2.5 Performance Measures

Students were surveyed throughout their project. In the survey, students were asked to evaluate their own and teammate performance. The performance measures focus on twelve aspects that are essential to the success of group projects, and they are listed in Table 4. Each measure can take on values of 1, 2, 3 and 4, with 1 being strongly disagree, and 4 being strongly agree. To eliminate the potential bias of self-evaluation, we subtract individual's own score and use the average of evaluation scores from the other team members as the individual's final score. The average of these 12 measures is generated to demonstrate the overall performance level.

Table 4: Description of Performance Measures

Notation	Description
l21	Completed his/her tasks with the expected quality
l22	Completed his/her tasks to achieve the overall project goals
l23	Collaborated with team members from other disciplines to achieve the project goals
l24	Provided information to team members from other disciplines when needed
l31	Adapted well to changes in the project that altered how he/she completed his/her task
l32	Coped with unforeseen demands placed on him/her
l33	Understood well how to deal with changes in the project to achieve the project goals
l34	Coped with changes to the project that altered how members from different disciplines collaborated on project goals
l41	Contributed new, improved ways to develop his/her tasks
l42	Initiated changes to the ways in which his/her tasks were done that helped accomplish project goals
l43	Created innovative solutions to improve the project quality
l44	Developed alternative solutions to achieve the project goals ahead of time

3 RESULTS AND DISCUSSION

The unit of observation is individual at each meeting. We apply ordinary least squares regressions to answer the first and second research questions: Whether being familiar with online learning affects engagement and performance in project teams, and if so, whether this effect is heterogeneous by race and gender. In Model (1), the coefficient of the interaction terms between familiarity and female (β_3) captures potential differences between male and female students. Similarly, the coefficient of the interaction terms between familiarity and race indicator (β_{11}) in Model (2) captures differences by race. Due to data limitations, only White and Asian students show up for both pre and post periods. The linear models to be estimated are as follows:

$$y_i = \beta_0 + \beta_1 * familiarity + \beta_2 * female + \beta_3 * female * familiarity + \beta_4 * familiarity * size \\ +\beta 5 * i.race + \beta_6 * size + \beta_7 * semesters \\ +\beta_8 * technical + \beta_9 * social + \beta_{10} * undergraduate + \epsilon_i \tag{1}$$

$$y_i = \beta_0 + \beta_1 * familiarity + \beta_2 * female + \beta_3 * female * familiarity + \beta_4 * familiarity * size \\ +\beta 5 * i.race + \beta_6 * size + \beta_7 * semesters + \beta_8 * technical + \beta_9 * social \\ +beta_{10} * undergraduate + \beta_{11} * \text{asian} * \text{familiarity} + \epsilon_i \tag{2}$$

The analysis for performance uses model (1) as well, except for changing the dependent variable to be the performance measure.

3.1 Gender and Race Heterogeneous Effects

In the regressions, we calculate the standard error in two ways: the first one is robust standard error, which is robust to misspecification if observations are independent. The second one is clustered standard error, which allows for intragroup correlation. Regression results (1), (2) and (3) use robust standard error, while results (4), (5) and (6) use clustered standard error at the group level.

The coefficients of the interaction between the variables familiarity and female are significantly negative at the 10% significance level under results (1) and (2). This indicates that the effect of being familiar with the online learning format on meeting engagement differs by gender: the participation of female students decreases more than that of their male counterparts. As engagement can be further divided into giving and asking for information, we then examine which of the two channels contributes to this effect. The results in Table 4 show that the coefficients on the interaction of familiarity and female are significant for examining duration of time when giving information (columns 11 and 13) but not when asking for information (columns 12 and 14). The evidence indicate that these gender differences are concentrated in women's lower propensity to give information relative to men.

In terms of differences by race, we find that the engagement for Asian and Hispanic/Latino students are significantly lower than that for White students at the beginning of the COVID-19 pandemic. However, as students became familiar with the online learning format over time, these race gaps became smaller between Asian and White students. This conclusion can be seen from the coefficient on the interaction term between Asian and familiarity. We cannot estimate the coefficient on Latino or Black with familiarity for lack of participation by Hispanic and Black students in both pre- and post-periods.

Table 3: Regression Results on Student Engagement

	(1) pdur	(2) pdur_s1	(3) pdur_s2	(4) pdur	(5) pdur_s1	(6) pdur_s2
familiarity=1	10.39 (15.91)	0.512 (0.784)	-0.0788 (0.717)	10.39 (9.586)	0.512 (0.472)	-0.0788 (0.516)
female=1	3.592 (4.161)	0.177 (0.205)	0.144 (0.178)	3.592 (6.062)	0.177 (0.299)	0.144 (0.282)
familiarity=1 # female=1	-8.956* (5.168)	-0.441* (0.255)	-0.336 (0.225)	-8.956 (9.660)	-0.441 (0.476)	-0.336 (0.439)
familiarity=1 # team size	-1.781 (2.800)	-0.0877 (0.138)	0.0144 (0.124)	-1.781 (1.232)	-0.0877 (0.0607)	0.0144 (0.0637)
Asian	-9.910*** (3.309)	-0.488*** (0.163)	-0.456*** (0.157)	-9.910** (4.139)	-0.488** (0.204)	-0.456* (0.220)
Black	3.936 (4.666)	0.194 (0.230)	0.222 (0.227)	3.936 (7.330)	0.194 (0.361)	0.222 (0.324)
Hispanic or Latino	-8.225*** (2.690)	-0.405*** (0.133)	-0.374** (0.161)	-8.225** (3.747)	-0.405** (0.185)	-0.374** (0.161)
team size	-2.521 (1.590)	-0.124 (0.0783)	-0.0190 (0.0685)	-2.521*** (0.852)	-0.124*** (0.0420)	-0.0190 (0.0399)
semesters	-0.0750 (0.315)	-0.00370 (0.0155)	-0.00416 (0.0173)	-0.0750 (0.398)	-0.00370 (0.0196)	-0.00416 (0.0199)
technical	-2.276 (4.390)	-0.112 (0.216)	-0.0439 (0.198)	-2.276 (6.834)	-0.112 (0.337)	-0.0439 (0.324)
social	-1.136 (6.912)	-0.0560 (0.341)	0.0134 (0.313)	-1.136 (4.512)	-0.0560 (0.222)	0.0134 (0.223)
Asian_familiarity	8.934** (4.384)	0.440** (0.216)	0.312 (0.210)	8.934 (7.220)	0.440 (0.356)	0.312 (0.391)
undergraduate	-0.211 (2.835)	-0.0104 (0.140)	0.00686 (0.135)	-0.211 (3.802)	-0.0104 (0.187)	0.00686 (0.174)
Constant	37.77** (17.44)	0.963 (0.859)	0.309 (0.758)	37.77*** (12.62)	0.963 (0.622)	0.309 (0.618)
Observations	468	468	468	468	468	468

Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

Table 4: Regression Results on Which Channel(s) Contributes to Gender Heterogeneous Effect

	(7) givepdur	(8) askpdur	(9) givedur	(10) askdur	(11) givepdur	(12) askpdur	(13) givedur	(14) askdur
familiarity=1	22.86* (12.90)	0.971 (3.469)	7.175 (5.100)	-0.206 (1.077)	22.86*** (5.462)	0.971 (1.932)	7.175** (3.106)	-0.206 (0.818)
female=1	2.807 (3.458)	0.287 (0.633)	1.620 (1.680)	0.141 (0.291)	2.807 (4.838)	0.287 (0.773)	1.620 (2.085)	0.141 (0.295)
familiarity=1 # female=1	-6.534 (4.278)	-1.088 (0.948)	-3.211* (1.871)	-0.331 (0.394)	-6.534 (7.525)	-1.088 (1.596)	-3.211 (2.958)	-0.331 (0.758)
familiarity=1 # size	-3.163 (2.390)	-0.146 (0.637)	-0.815 (0.749)	0.138 (0.161)	-3.16*** (0.644)	-0.146 (0.401)	-.815** (0.367)	0.138 (0.133)
Asian	-3.622* (1.882)	-0.930* (0.537)	-0.887 (0.753)	-0.203 (0.217)	-3.622 (3.746)	-0.930 (0.766)	-0.887 (1.331)	-0.203 (0.294)
Black	5.027 (3.871)	-1.083 (0.973)	0.851 (1.522)	-0.666** (0.286)	5.027 (6.413)	-1.083 (0.785)	0.851 (2.463)	-0.666* (0.319)
Hispanic or Latino	-7.6*** (2.410)	-1.8*** (0.465)	-1.4** (0.637)	-.459*** (0.158)	-7.59*** (2.512)	-1.8** (0.661)	-1.396 (0.995)	-0.460 (0.285)
team size	-1.345 (1.345)	-0.130 (0.285)	-0.287 (0.630)	0.0445 (0.122)	-1.345** (0.518)	-0.130 (0.136)	-0.287 (0.405)	0.0445 (0.0923)
semesters	-0.285 (0.253)	0.25*** (0.0789)	-0.0566 (0.113)	0.087*** (0.0313)	-0.285 (0.364)	0.25*** (0.082)	-0.0566 (0.158)	0.0873*** (0.0274)
technical	0.0176 (3.879)	-0.632 (1.002)	0.297 (1.724)	-0.145 (0.400)	0.0176 (5.067)	-0.632 (0.951)	0.297 (1.874)	-0.145 (0.452)
social	-0.573 (6.151)	0.714 (1.342)	0.691 (2.469)	0.569 (0.455)	-0.573 (3.351)	0.714 (0.780)	0.691 (1.403)	0.569 (0.328)
undergraduate	1.164 (2.425)	-0.890 (0.646)	0.332 (1.113)	-0.304 (0.269)	1.164 (2.942)	-0.890 (0.579)	0.332 (1.259)	-0.304 (0.312)
meeting time in minutes			0.16*** (0.0368)	0.036*** (0.00875)			0.16*** (.0196)	0.036*** (0.00484)
Constant	22.40 (15.09)	2.419 (3.310)	-0.441 (7.526)	-1.472 (1.545)	22.40*** (5.949)	2.419 (1.738)	-0.441 (4.012)	-1.472 (1.057)
Observations	468	468	468	468	468	468	468	468

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.2 How Does Being Familiar with Online Meeting Affects Students' Performance?

By using Model (1), we find that most measures in Table 2 increase after students became familiar with the online meeting format, which in sum increases the average of the 12 ratings by 0.755 (out of 4). No measure had a significantly negative coefficient for *familiarity*. Another consistent observation is that the cross evaluations for Asian students fell a lot during the time of disruption, and this is additional evidence that online meetings have differential effects by race.

Table 5: Regression Results on How Familiarity with Online Format Affects Student Performance

	overall
familiarity=1	0.755***
	(0.280)
female=1	0.0428
	(0.142)
familiarity=1 # female=1	-0.168
	(0.284)
Asian	-0.401**
	(0.186)
Black	0.0269
	(0.0686)
Hispanic or Latino	0.0241
	(0.236)
GPA	0.275
	(0.191)
team size	0.185**
	(0.0928)
semesters	-0.0161
	(0.0140)
technical	0.0140
	(0.215)
social	0.493*
	(0.270)
undergraduate	0.207
	(0.154)
Asian_familiarity	-0.0232
	(0.298)
Constant	0.915
	(1.409)
Observations	93

3.3 Are Meetings Longer or Shorter After Being Familiar with Online Meeting Format

First, Figure 1 demonstrates total meeting time in different semesters. There is no compelling evidence that the total time differs across semesters. Trends in the race and gender effects we report above are not driven by changes in meeting length (e.g., women talking more during longer meetings than during shorter meetings).

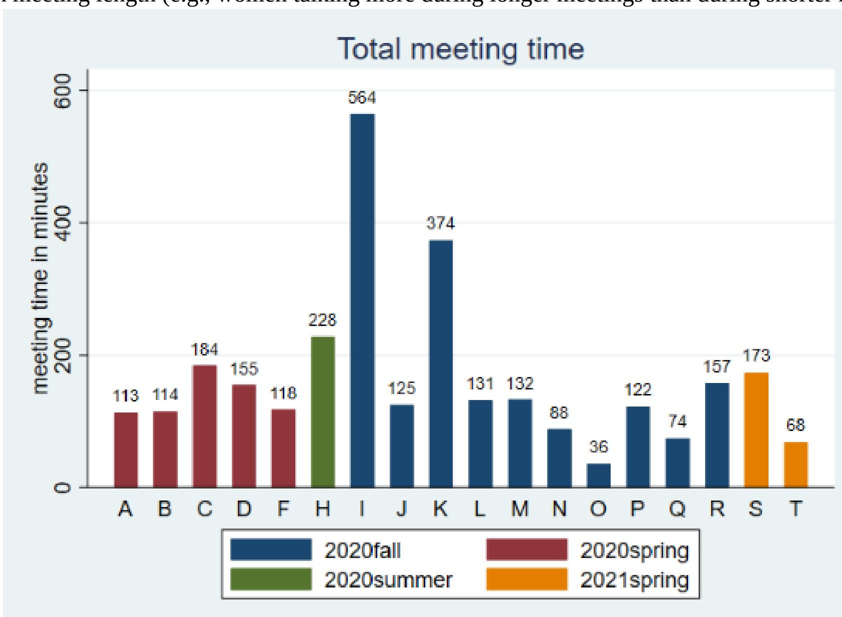

Figure 1: Total meeting time in different semesters

Since total time is affected by meeting occurrence, a better metric to compare meeting length is the average duration per meeting. We then use this metric and depict Figure 2, which again shows no evidence that average meeting time differs before and after the time of disruption (i.e., before and after Summer 2020).

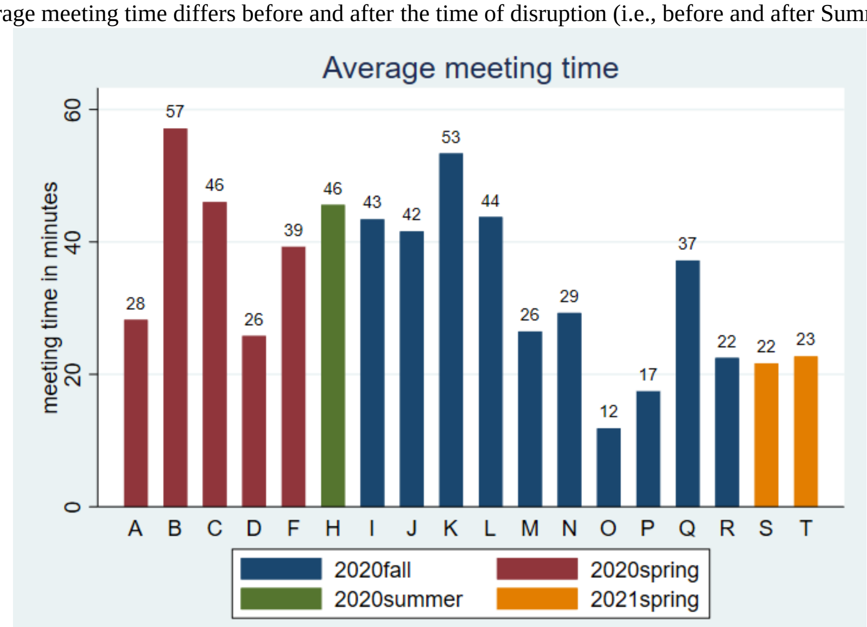

Figure 2: Average meeting time in different semesters

The next question is whether there is a clear pattern of average meeting time with type of classes. All teams are separated into one of the three categories: technical, social science, and both. One drawback is that we do not have full coverage of all three types in each semester, and the results can be affected by extreme values as some categories only have one team in some semesters. We have one preliminary conclusion from Figure 3: "Technical & social (hybrid)" teams have longer average meeting time, compared with the other two categories. There is no clear pattern between "technical" and "social" teams.

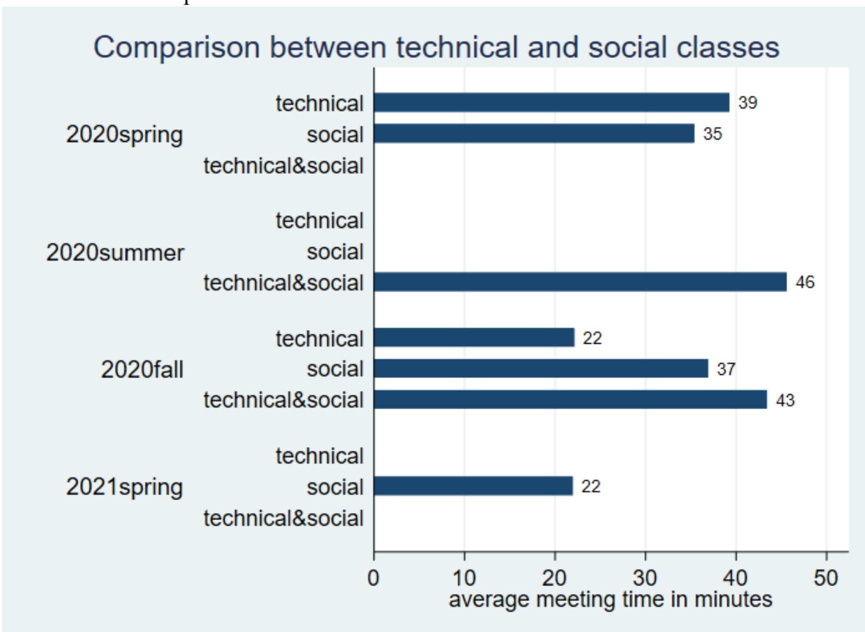

Figure 3: Comparison of average meeting time between technical and social classes

4 CONCLUSIONS

From a unique dataset collected at a large Big Ten university from Spring 2020 to Fall 2021, we examine how the COVID-19 disruption and the gradual transition to online meetings affected students' participation and performance in project teams. There is evidence that female and minority students suffered more from the transition to online meetings. For female students, the decrease in giving information during online communication contributed to the negative effect. The participation gap between Asian and White students remained but decreased after they became more familiar with online learning format.

We also check how meeting time changed since the time of disruption. There is no evidence that either total or average meeting time differs after online meetings become the norm, but given the wide range of teams we investigate, we can conclude that hybrid teams (project teams that have both technical and social components) had longer average meeting time, compared with purely technical or social teams.

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