The effect of having your camera on on performance in an online lecture

Lucas Mears, Sharon Zhong, Shreya Moola, Wendy Wang

12/9/2020

Introduction

During this pandemic, online classes have been a prevalent part of the learning process for the student body. However, there has been concern on ensuring students focus on the subject taught. The variety of entertainment choices, everyday distractions, and the potential lack of motivation means schools are struggling to keep students focused. Students in online courses are more likely to multitask in non-academic work compared to their peers in face-to-face courses (Lepp, Barkley, Karpinski, 2019). An abundance of research demonstrates that multitasking reduces learning. Ellis, Daniels, and Jauregui (2017) conclude that multitasking during class is likely to result in lower grade performance. A decade of data also reveals that heavy multitaskers have reduced memory compared to light multitaskers (Wagner & Uncapher, 2018).

In the online learning environment, the three dimensions of social presence – online communication, social context, and interactivity – are considered important elements (Tu & McIsaac, 2002). Students' sense of distance can impact their ability to learn. Video-based communication helped students feel that their instructors were more real and present, impacting instructor social presence (Borup, West, Graham, 2011).

Despite assumed benefits of cameras in synchronous online classes, little is known about the effect of webcams on student performance. We were interested in whether keeping your camera on would help minimize aforementioned distractions and improve focus. We believed that turning students' cameras on during online classes would improve their focus on the subject taught and students who had their cameras on would score better than students who had their cameras off. The implications of this study can be useful to students, instructors, administrators, and other academic stakeholders, about mandating webcams in an online learning environment.

To observe this, we created an experiment with 56 undergraduate college students to test whether their camera being on or off impacted their quiz performance. These participants had to watch a 2 minute recorded lecture and were given a Qualtrics survey about the contents of the lecture. All original volunteers were randomly assigned to the control group (camera off) or the treatment group (camera on).

```r
library(data.table)
library(ggplot2)
library(tidyverse)
library(pwr)
library(lfe)
library(modelsummary)
library(stargazer)
library(broom)
library(corrr)
library(dplyr)
library(knitr)
library(kableExtra)
```

```r
library(readr)
library(tidyr)

#data entering & cleaning
control <- fread('Data/BA472_Control.csv')
treatment <- fread('Data/BA472_Treatment.csv')
subjects <- fread('Data/SignupData.csv')
questions <- fread('Data/questions.csv')
allsignups <- fread('Data/allsignups.csv')

control <- control[, score := Q1_Correct+Q2_Correct+Q3_Correct+Q4_Correct+Q5_Correct+
                     Q6_Correct+Q7_Correct+Q8_Correct]
treatment <- treatment[, score := Q1_Correct+Q2_Correct+Q3_Correct+Q4_Correct+Q5_Correct+
                         Q6_Correct+Q7_Correct+Q8_Correct]

control <- control[, treatment := 0]
treatment <- treatment[, treatment := 1]

total<- rbind(control, treatment)
colnames(total)[2] <- 'Name'
colnames(total)[3] <- 'Email'
colnames(total)[1] <- 'Duration'

total <- inner_join(total, subjects, by='Name')
total <- total %>% select(-c(`Email.y`,`treatment`))
colnames(total)[3] <- 'Email'
```

Method

Participants

Since the goal of the experiment was to observe the effect of having your camera on in class, we decided undergraduate students would make the best subjects. Our initial method to recruit participants was by posting the picture in Figure 1 on our personal instagram stories. We also personally messaged our friends and classmates at BU as well as at other universities. Additionally, we posted messages on the 'Boston University Class of 2021', 'Boston University Class of 2022', 'Boston University Class of 2023', and 'Boston University Class of 2024' Facebook pages. People who were interested in participating were required to fill out a Google Form that detailed the time, date, etc. of the experiment as well as asked them their name, gender, age, and whether or not they attended Boston University, and took Zoom classes this semester. We also made sure to have participants check a box that stated that they were aware that they might have to turn their camera on. The Google Form (see Figure 2) also automatically collected the email addresses people used to fill out the form, giving us an efficient way to contact the signups later. We closed the form 4 days prior to the experiment and had a total of 71 signups across the ages of 18 to 22. Out of the 71, 52 are BU students and 69 are taking a class on Zoom at the moment. Additionally, 45 identify as female and 26 identify as male.

Although this sampling method was convenient, there are a few biases that emerge when recruiting only people we personally know. The first and most obvious is that the sample is not representative of college students across the United States. Since BU is in the northeast and all members of the group are from New York and New Jersey, a majority of the participants also go to colleges in the area. We also had a disproportionate number of Business majors sign up for the study since we personally approached a lot of classmates. This threatens the external validity of our results and makes it more difficult to apply our findings to a larger group. Since people chose whether or not to participate in the study, we can observe some effects of self-selection bias as well. Fortunately, we were able to randomize everyone into the control or treatment group in an attempt to avoid selection bias in the study.

Randomization

To decide which participants would be in the control or treatment group, we decided to randomize by blocking on certain characteristics to have greater statistical power. Using the answers we received from the Google Form, we blocked participants into BU and non-BU groups. Upon doing that, we then blocked on gender within each of these groups. Finally, we used the rand() function to assign a 1 or 0 each participants in each category. We chose to block on these characteristics because there were a disproportionate number of BU students who signed up for the study compared to non-BU students. After blocking on those, we realized there was a disproportionate number of females in each group. Thus, we decided to block on gender as well.

Pre-Experiment Randomization Check

After blocking the participants into the control or treatment group, we had to ensure that the groups were randomized. We did this by running regressions of gender, age, whether someone was taking classes on Zoom, and whether or not they attend Boston University on whether or not the participants were in the treatment group. Ideally, we would have also randomized some sort of intelligence factor to ensure that the groups were equally intelligent and that one group's superior intellect would not change the result of the quiz we ask at the end. However, while we recognize that this would have been a valuable variable to check our randomization on, we could not do this in an ethical way for these participants such as asking for sensitive information like GPA. The results of these regressions are below.

```
sample <- lm(Treatment ~ `Gender Dummy`, allsignups)
sample %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                          "P-Value"), digits = c(0, 3, 3, 3, 3), align ='c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	0.556	0.075	7.385	0.000
‘Gender Dummy‘	-0.094	0.124	-0.756	0.452

```
sample1 <- lm(Treatment ~ `BU Dummy`, allsignups)
sample1 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                          "P-Value"), digits = c(0, 3, 3, 3, 3), align ='c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	0.526	0.116	4.527	0.000
‘BU Dummy‘	-0.007	0.136	-0.052	0.959

```
sample2 <- lm(Treatment ~ `Zoom Dummy`, allsignups)
sample2 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                          "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	0.000	0.353	0.000	1.000
‘Zoom Dummy‘	0.536	0.358	1.499	0.138

```
sample3 <- lm(Treatment ~ `Age 19` + `Age 20` + `Age 21` + `Age 22`, allsignups)
sample3 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                          "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	0.571	0.187	3.064	0.003
‘Age 19‘	0.429	0.528	0.812	0.419
‘Age 20‘	0.065	0.239	0.272	0.786
‘Age 21‘	-0.134	0.200	-0.671	0.505
‘Age 22‘	0.429	0.309	1.386	0.171

These tables show that we randomized our variables well. None of the variables are statistically significant at the 90% confidence level, as their confidence intervals do contain 0 and the magnitude of their t-stat is less than 1.64. This means we can reject, with 90% certainty, that none of these characteristics made people more likely to be in the treatment. Even though we could not randomize for some sort of intelligence factor, the fact that all other variables were successfully randomized is encouraging that there is no bias in one group versus another.

Procedure

Upon taking into account that we had a few sources of bias already present from the sampling, we wanted to be extremely careful to avoid any other forms of unnecessary bias. For example, to avoid time bias, we made sure that the treatment and control groups would be participating at the same exact time.

After randomizing the participants into the control and treatment groups, we sent them an email containing the Zoom link and the directions for either keeping their camera on or off during the experiment. To ensure consistency, we drafted identical emails for both groups with the only difference being the Zoom link and whether or not their cameras should stay on. A copy of our email can be seen in Figure 3. We also made sure to resend the email an hour before the experiment as a reminder. In the second email, we added a sentence requesting people to join the Zoom meeting from separate rooms if they were living with someone else who was also participating (see Figure 4).

The next challenge was to figure out what topic we wanted to lecture the two groups on. Of course we wanted to keep the lectures consistent between the groups and wanted to talk about something that participants likely would not have previous knowledge about and could not easily search up. To address these concerns, we decided to create a 2 minute video of Lucas lecturing about a fake Roman Revolution battle. The video (Figure 5) would be played to both groups to ensure that they would hear the exact same things and there would be no extra noise related to the lecture itself, and the fact that the video was not a real historical event would ensure people could not search up answers.

Following the creation of the video, we created two separate Qualtrics surveys containing the same 8 questions about the lecture. We made sure to include a variety of questions including specific small details/facts (ex. What year did the battle occur?) as well as more contextual/storyline based questions (ex. Which event happened first?). Additionally, we included a question that was not actually answered in the lecture to gauge overall ‘paying attention’. Below is a table detailing the breakdown of the questions.

```r
questions[Number %in% c('Q1', 'Q2', 'Q5', 'Q7'),Category:= 'Small Detail']
questions[Number %in% c('Q3', 'Q4', 'Q6'),Category:= 'Overall Storyline']
questions[Number %in% c('Q8'),Category:= 'Paying Attention']
questions %>% kable(align = 'c')
```

Number	Question	Category
Q1	What was the name of the Battle?	Small Detail
Q2	What year did the battle occur in?	Small Detail
Q3	Why were they called the Spurnites?	Overall Storyline
Q4	Which event happened first?	Overall Storyline
Q5	What was Morca Crute’s wife’s name?	Small Detail
Q6	How did the Metalites react to Caeser’s death?	Overall Storyline
Q7	Who was the mayor of the town?	Small Detail
Q8	What crops did the farmers have?	Paying Attention

We then decided to create a script to guarantee that both groups heard the same exact things during the experiment.

To ensure the experiment would run efficiently and smoothly, we ran a pilot of the experiment with a friend playing the role as a participant in the treatment group. We ran through the exact script, timing, quiz, video, and everything else we planned to do in the real experiment. The pilot raised a number of considerations that we took into account for the experiment. First, it was important to run the control and the treatment at the same time on the same date and have all of the components run roughly identical to each other. During the pilot, we had forgotten to share computer audio and the video would not play. While that is a quick fix, it would have disrupted the flow during the real experiment and it would have brought another variable into one of the groups that the other group would not have. Also, at the end of the experiment our participant put into the general chat that he was finished with the quiz. Our instructions specifically say to message the host privately so that we can confirm the quiz submission, so as to not influence the other participants seeing that someone is done. The fact that he told the hosts he was done in the general chat showed us that we had to make modifications to our script to make it more explicit that they should private message the host, and we also changed the settings in the Zoom meetings so that participants do not have the option to use the general chat. Once again, without this pilot we may not have done that and we may have run into the issue of people chatting with each other and influencing everyone taking the quiz. Thankfully, these modifications ensured that our experiment ran smoothly and we had no issues with sharing sound or with the use of the chat function.

Experiment Run Through

During the running of our actual experiment, we opened the Zoom calls at 2:58pm to give people time to join. Immediately, participants saw the video paused on an introduction slide mentioning that we would begin at 3pm so everyone was prepared to wait. Then at 3pm, we began following the script shown in Figure 6. The scripts were identical for both groups with the only difference being the names of the moderators and whether their cameras should stay on or off. Once we ensured that everyone was following the directions, we played the video and told them to listen carefully. Immediately after the lecture ended, the video displayed a second slide telling everyone that they must complete the survey using the link provided and must check in with a specific host to make sure we received their submission prior to leaving. Once again, to ensure consistency, we had a pre-written thank you message that we sent to each participant once we checked that we could see their responses.

Post-Experiment Randomization Check

We ended up with 56 observations from the experiment, as we had a number of people who did not come to the experiment. Therefore, we wanted to confirm that the groups who came and participated in the experiment were still diverse and random, and that no characteristics that we checked before the experiment were statistically significant on being in the treatment. We ran the regressions we had done before the experiment again with the participants who came to the experiment. The results are in the table below.

```
test <- lm(Treatment ~ Gender, total)
test %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                        "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	0.600	0.084	7.138	0.000
Gender	-0.219	0.137	-1.596	0.116

```
test1 <- lm(Treatment ~ BU, total)
test1 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                         "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	0.429	0.135	3.168	0.003
BU	0.119	0.156	0.762	0.449

```
test2 <- lm(Treatment ~ Zoom, total)
test2 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                          "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	0.000	0.504	0.000	1.000
Zoom	0.527	0.508	1.037	0.304

```
test3 <- lm(Treatment ~`Age 20` + `Age 21` + `Age 22`, total)
test3 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                          "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	0.333	0.283	1.178	0.244
‘Age 20‘	0.381	0.338	1.126	0.265
‘Age 21‘	0.119	0.293	0.406	0.686
‘Age 22‘	0.667	0.374	1.780	0.081

It is important to note that none of the people who signed up who were aged 19 came to the experiment, so that row of the table was dropped. Our randomization held for most values, however we ran into an issue with the category of being aged 22. This variable was now statistically significant on the 90% confidence level (the p-value is .081). This means that for those who came to the experiment, participants aged 22 were statistically significantly more likely to be in the treatment group compared to those who were aged 18. This shows the importance of running the randomization checks again after the experiment since the attendees do not match the initial participants list we had. We adjusted for this in the regressions we ran as appropriate.

Data Analysis

With the data we have, we can run a number of regressions to analyze the performance of our participants in a number of different ways. We begin with a simple regression analyzing the main effect we are researching, the effect of being in the treatment (having your camera on) on the score of the quiz. Therefore, we ran the following regression with the following results:

```
reg1 <- lm(score ~ Treatment, total)
R2reg1 <- data.frame(summary(reg1)$r.squared,summary(reg1)$adj.r.squared)
colnames(R2reg1)[1]<- 'R Squared'
colnames(R2reg1)[2]<- 'Adjusted R Squared'
reg1 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                         "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	4.000	0.332	12.044	0.000
Treatment	0.379	0.462	0.822	0.415

```
R2reg1 %>% kable(align = 'c')
```

R Squared	Adjusted R Squared
0.0123539	-0.0059358

The interpretation of this regression is that, on average, those in the treatment group scored .379 points higher compared to those in the control group. This would indicate a positive relationship between having your camera on and scoring better, however with a p-value of .415 this variable is not statistically significant. However, this simple regression might not be our best model to analyze this variable. Due to the complexity of age 22 being statistically significant on being in the treatment, there are other regressions that we had to run and check in the process of creating a full model. Therefore, we decided to run a regression of age on score- if there was little to no effect of age on the y variable of score, then the fact that 22 year olds were more likely to be in the treatment group would not be an issue and we can use the simple regression above as the basis of our interpretation of analysis. Therefore, we ran this background regression with the following results:

```r
reg2 <- lm(score ~`Age 20` + `Age 21` + `Age 22`, total)
reg2 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                        "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	5.333	0.991	5.383	0.000
‘Age 20‘	-1.190	1.184	-1.005	0.319
‘Age 21‘	-1.095	1.026	-1.068	0.290
‘Age 22‘	-2.333	1.311	-1.780	0.081

This regression says that, on average, 20 year olds average 1.19 points less than 18 year olds (which is the omitted variable), 21 year olds score 1.10 points less than 18 year olds on average, and 22 year olds score 2.33 points less than 18 year olds on average. With p-values of .32 and .29 respectively, the ages of 20 and 21 are not statistically significant in this regression. However, with a p-value of .081, age 22 is statistically significant on the 90% confidence level. We are 90% confident that being aged 22 makes you score worse compared to 18 year olds on average.

What we see here was something that our group did not expect- as stated before, being 22 years old made you statistically significantly more likely to be in the treatment group compared to 18 year olds (a p value of 0.081) indicates this. We can see in the above regression that being 22 years old is also statistically significant on the score you received on the quiz. We now have a variable, being 22 years old, that is statistically significant on our y variable (score) as well as our x variable (treatment). 22 year olds were more likely to be in the treatment group, and 22 year olds were more likely to do poorly on the quiz. Therefore, the simple regression of just the effect of treatment on score suffers from omitted variable bias- if we were to analyze the simple regression alone, the negative effect of being 22 years old would be falsely attributed to being in the treatment group due to the fact that 22 year olds were more likely to be in the treatment group. To be able to hold age constant and analyze just the effect of being in the treatment on score, we decided to do a larger regression that includes age and being in the treatment as the x variables. That regression and the interpretation can be found below:

```r
reg3 <- lm(score ~ Treatment + `Age 20` + `Age 21` + `Age 22`, total)
R2reg3 <- data.frame(summary(reg2)$r.squared,summary(reg2)$adj.r.squared)
colnames(R2reg3)[1]<- 'R Squared'
colnames(R2reg3)[2]<- 'Adjusted R Squared'
reg3 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                        "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	5.109	0.995	5.136	0.000
Treatment	0.674	0.481	1.402	0.167
‘Age 20‘	-1.447	1.188	-1.219	0.229
‘Age 21‘	-1.176	1.018	-1.155	0.253
‘Age 22‘	-2.783	1.338	-2.080	0.043

```r
R2reg3 %>% kable(align = 'c')
```

R Squared	Adjusted R Squared
0.059546	0.005289

This full model removes the omitted variable bias existent in the simple regression we ran before, as we can now hold age constant. The R^2 also increases from .012 to an Adjusted R^2 of .023, indicating that this full regression model is a better predictor of score compared to the simple regression model (the simple regression model explains approximately 1.2% of the variance of score, the full model explains approximately 2.3% of the variance of score), which is what we expected now that we can hold age constant. Now that the omitted variable bias is removed, we can interpret the treatment coefficient more accurately. Holding age constant, on average those in the treatment group score .67 points more compared to the control group. However, with a p-value of .167, this coefficient is still not statistically significant (although, compared to the original p-value of .415 we can see it become more significant). Age 22 is still statistically significant in this full model with a p-value of .043, and while this is interesting to note age is not the variable we were conducting this research on therefore we note it is statistically significant however we did not conduct further analysis as we cannot think of a logical reason why age would have this effect that fits into the question we are trying to answer.

Our final conclusion as it pertains to the effect of being in the treatment on the score on the quiz is that, on average while holding age constant, having your camera on increased your score by approximately .67 points compared to those who kept their cameras off. However, this value is not statistically significant and therefore we cannot say with statistical confidence that having your camera on has a positive effect on your score.

The following table shows all of these regressions together:

```r
scoreregs <- stargazer(reg1, reg2, reg3, type = 'text',
                       title = 'Regression Results on Score', align = TRUE,
                       dep.var.labels = c('Total Question Score'),
                       no.space=TRUE)
```

```
Regression Results on Score
======================================================================
                                   Dependent variable:
                   ---------------------------------------------------
                                  Total Question Score
                         (1)               (2)               (3)
----------------------------------------------------------------------
Treatment               0.379                               0.674
                       (0.462)                             (0.481)
`Age 20`                                 -1.190            -1.447
                                         (1.184)           (1.188)
`Age 21`                                 -1.095            -1.176
                                         (1.026)           (1.018)
`Age 22`                                 -2.333*           -2.783**
                                         (1.311)           (1.338)
Constant               4.000***          5.333***          5.109***
                       (0.332)           (0.991)           (0.995)
----------------------------------------------------------------------
Observations             56                56                56
R2                      0.012             0.060             0.094
Adjusted R2            -0.006             0.005             0.023
```

```
Residual Std. Error  1.726 (df = 54)    1.716 (df = 52)    1.700 (df = 51)
F Statistic         0.675 (df = 1; 54) 1.097 (df = 3; 52) 1.330 (df = 4; 51)
============================================================================
Note:                                              *p<0.1; **p<0.05; ***p<0.01
```

The next variable we wanted to analyze to gain a full picture of how both groups did in terms of performance was the time that it took them to finish the quiz, a variable we are calling duration. We are following the same procedure on this variable as we did above, therefore we started with a simple regression of the effect of being in the treatment on duration. The results of this regression are:

```
reg4 <- lm(Duration ~ Treatment, total)
R2reg4 <- data.frame(summary(reg4)$r.squared,summary(reg4)$adj.r.squared)
colnames(R2reg4)[1]<- 'R Squared'
colnames(R2reg4)[2]<- 'Adjusted R Squared'
reg4 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                   "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	95.889	8.109	11.824	0.000
Treatment	6.180	11.269	0.548	0.586

```
R2reg4 %>% kable(align = 'c')
```

R Squared	Adjusted R Squared
0.0055387	-0.0128772

The interpretation of this regression is that, on average, being in the treatment resulted in you taking six seconds longer on the quiz compared to those in the control group. However, with a P value of .59 this is not close to statistically significant, and we really cannot say either way whether or not being in the treatment has an effect on the duration of the quiz. This is further supported by a very small R^2 of .006, showing that being in the treatment caused almost none of the variance of duration. Still, we wanted to continue with the analysis of the variable so we ran a regression of age on duration to ensure that there was no omitted variable bias. The result of that regression is:

```
reg5 <- lm(Duration ~ `Age 20` + `Age 21` + `Age 22`, total)
reg5 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                    "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	138.000	23.852	5.786	0.000
‘Age 20‘	-29.286	28.509	-1.027	0.309
‘Age 21‘	-44.810	24.689	-1.815	0.075
‘Age 22‘	-23.000	31.553	-0.729	0.469

The interpretation of this regression is that, on average, 20 year olds took 29.29 less seconds to complete the quiz compared to 18 years old, 21 year olds took 44.81 less seconds compared to 18 year olds, and 22 year olds took 23 less seconds compared to 18 year olds to finish the quiz. Of these ages, only age 21 is statistically significant with a p-value of .0753 (statistically significant on the 90% confidence level). Therefore, we should not have omitted variable bias as no variable is impacting both our x variable of treatment and our y variable of duration. It is true that age 22 is still statistically significant on treatment, and age 21 is statistically significant on duration, but these are two different variables so the effect of one of these is not being incidentally captured by our x variable of treatment. Still, however, with our R^2 being so low, we decided to run the full model to see if the Adjusted R^2 would be higher and give us a better model to look at for our final conclusion. Therefore, we ran the regression below:

```r
reg6 <- lm(Duration ~ Treatment + `Age 20` + `Age 21` + `Age 22`, total)
R2reg6 <- data.frame(summary(reg6)$r.squared,summary(reg6)$adj.r.squared)
colnames(R2reg6)[1]<- 'R Squared'
colnames(R2reg6)[2]<- 'Adjusted R Squared'
reg6 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                        "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	136.725	24.379	5.608	0.000
Treatment	3.825	11.787	0.324	0.747
‘Age 20‘	-30.743	29.106	-1.056	0.296
‘Age 21‘	-45.265	24.944	-1.815	0.075
‘Age 22‘	-25.550	32.784	-0.779	0.439

```r
R2reg6 %>% kable(align = 'c')
```

R Squared	Adjusted R Squared
0.0813917	0.009344

The interpretation of this regression is that, on average, those in the treatment spent 3.83 more seconds on the quiz compared to the control group holding age constant. It also states that 20 year olds took 30.74 seconds less on the quiz compared to 18 year olds on average holding treatment constant, 21 year olds took 45.27 seconds less on the quiz compared to 18 year olds on average holding treatment constant, and 22 year olds took 25.55 seconds less on the quiz compared to 18 year olds on average holding treatment constant. We see that the treatment variable changed a little, however with a p-value of .75 it became even less significant. The R^2 increased from .006 to an Adjusted R^2 of .009, so this model predicts the variance better, therefore for our conclusion we will use this full model despite the fact that we do not think our simple regression suffers from omitted variable bias. Age 21 is still statistically significant in this full model on the 90% confidence level, however as we mentioned before age is not the variable we are analyzing so it is interesting to note but we did not conduct further analysis on it.

Our conclusion on being in the treatment and the effect that it has on duration is that, on average, those in the treatment took 3.83 seconds longer on the quiz compared to the control group on average holding age constant. However, with a p-value of .75 this variable is not statistically significant and we cannot conclude anything about duration from this model in terms of our experiment.

The following table shows all of these regressions together:

```r
durationregs <- stargazer::stargazer(reg4, reg5, reg6, type = 'text',
                                     title = 'Regression Results on Duration',
                                     align = TRUE,
                                     dep.var.labels = c('Duration (in Seconds)'),
                                     no.space=TRUE)
```

```
Regression Results on Duration
=============================================================================
                                        Dependent variable:
                     --------------------------------------------------------
                                       Duration (in Seconds)
                            (1)                (2)                 (3)
-----------------------------------------------------------------------------
Treatment                  6.180                                  3.825
                         (11.269)                               (11.787)
```

```
`Age 20`                                   -29.286          -30.743
                                           (28.509)         (29.106)
`Age 21`                                   -44.810*         -45.265*
                                           (24.689)         (24.944)
`Age 22`                                   -23.000          -25.550
                                           (31.553)         (32.784)
Constant                 95.889***        138.000***       136.725***
                          (8.109)          (23.852)         (24.379)
----------------------------------------------------------------------------
Observations                56                56               56
R2                        0.006             0.079            0.081
Adjusted R2               -0.013            0.026            0.009
Residual Std. Error  42.138 (df = 54)  41.313 (df = 52)  41.673 (df = 51)
F Statistic         0.301 (df = 1; 54) 1.497 (df = 3; 52) 1.130 (df = 4; 51)
============================================================================
Note:                                           *p<0.1; **p<0.05; ***p<0.01
```

We also wanted to analyze how the treatment and control groups responded to different types of questions, therefore we designed two categories of questions. Questions 3, 4, and 6 are storyline questions, as they require the subject to recall a larger part of the overall lecture. Questions 1, 2, 5, and 7 are small details questions, as they focus on a very minute part of the lecture and require the subject to recall a specific detail mentioned in passing. We did not run a regression on Question 8 because although it was created as a way to see if people paid close enough attention to realize that it was never answered, we concluded that this alone was not a strong enough variable to gauge "paying attention." We started by running similar regression analysis on storyline questions as we did on the other two variables above. We began with our simple regression analyzing the effect of being in the treatment on storyline question scores (with a max score in this category being a three out of three). The regression gave us the following results:

```r
#storyline & small details
total[, smalldetails := (Q1_Correct +Q2_Correct +Q5_Correct +Q7_Correct)]
total[, storyline := (Q3_Correct +Q4_Correct +Q6_Correct)]

reg7 <- lm(storyline ~ Treatment, total)
R2reg7 <- data.frame(summary(reg7)$r.squared,summary(reg7)$adj.r.squared)
colnames(R2reg7)[1]<- 'R Squared'
colnames(R2reg7)[2]<- 'Adjusted R Squared'
reg7 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                        "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	1.630	0.184	8.847	0.000
Treatment	-0.078	0.256	-0.304	0.762

```r
R2reg7 %>% kable(align = 'c')
```

R Squared	Adjusted R Squared
0.0017125	-0.0167743

The interpretation of this regression is that those in the treatment scored .078 points less on the three storyline questions, on average, compared to those in the control group. This is another variable that is not close to statistically significant, with a p-value of .76. The R^2 of this model also indicates that this variable does not tell us anything significant, as the R^2 is only .002. After this simple regression, we once again wanted to see if there was potential omitted variable bias with age missing. We ran the following regression:

```r
reg8 <- lm(storyline ~ `Age 20` + `Age 21` + `Age 22`, total)
reg8 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                         "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	1.333	0.559	2.385	0.021
‘Age 20‘	0.238	0.668	0.356	0.723
‘Age 21‘	0.310	0.579	0.535	0.595
‘Age 22‘	-0.083	0.740	-0.113	0.911

This regression states that, on average, 20 year olds scored .24 more points on the three storyline questions compared to 18 year olds, 21 year olds scored .31 points more on the three storyline questions on average compared to 18 year olds, and 22 year olds scored .083 points less on average on the three storyline questions compared to 18 year olds. With p-values of .72, .60, and .91, none of these ages were statistically significant on the score. Therefore, omitted variable bias should not be an issue. However, due to the low R^2 of our simple regression, we wanted to run a full model incorporating age and treatment to see if the model was a better explanation for the variance in storyline questions. We ran the following regression:

```r
reg9 <- lm(storyline ~ Treatment + `Age 20` + `Age 21` + `Age 22`, total)
R2reg9 <- data.frame(summary(reg9)$r.squared,summary(reg9)$adj.r.squared)
colnames(R2reg9)[1]<- 'R Squared'
colnames(R2reg9)[2]<- 'Adjusted R Squared'
reg9 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                         "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	1.344	0.572	2.350	0.023
Treatment	-0.032	0.277	-0.117	0.907
‘Age 20‘	0.250	0.683	0.367	0.715
‘Age 21‘	0.313	0.585	0.535	0.595
‘Age 22‘	-0.062	0.769	-0.080	0.936

```r
R2reg9 %>% kable(align = 'c')
```

R Squared	Adjusted R Squared
0.0160002	-0.0611762

We decided that the full model was not better than the simple model for interpretation. The Adjusted R^2 is -.06 which indicates this full model has no predictive power, and none of the variables in the background model are statistically significant, therefore there is no omitted variable bias and we are using our initial simple regression model for our conclusion.

Therefore, using that simple model, our conclusion is that, on average, those in the treatment group score .078 less points on the storyline questions compared to the control group. However, with a p-value of .76 we cannot conclude that there is a positive or negative relationship as it is not statistically significant. Being in the treatment or the control group has no discernable impact on how you did on these questions.

The following table shows all of these regressions together:

```r
storylineregs <- stargazer::stargazer(reg7, reg8, reg9, type = 'text',
                                      title = 'Regression Results on Storyline Score',
                                      align = TRUE,
                                      dep.var.labels = c('Storyline Questions Score'),
                                      no.space=TRUE)
```

```
Regression Results on Storyline Score
=============================================================================
                                        Dependent variable:
                    ---------------------------------------------------------
                                     Storyline Questions Score
                           (1)                 (2)                 (3)
-----------------------------------------------------------------------------
Treatment                -0.078                                  -0.032
                         (0.256)                                 (0.277)
`Age 20`                                     0.238               0.250
                                            (0.668)             (0.683)
`Age 21`                                     0.310               0.313
                                            (0.579)             (0.585)
`Age 22`                                    -0.083              -0.062
                                            (0.740)             (0.769)
Constant                1.630***            1.333**             1.344**
                         (0.184)            (0.559)             (0.572)
-----------------------------------------------------------------------------
Observations               56                  56                  56
R2                        0.002               0.016               0.016
Adjusted R2              -0.017              -0.041              -0.061
Residual Std. Error  0.957 (df = 54)     0.968 (df = 52)     0.978 (df = 51)
F Statistic        0.093 (df = 1; 54) 0.277 (df = 3; 52) 0.207 (df = 4; 51)
=============================================================================
Note:                                             *p<0.1; **p<0.05; ***p<0.01
```

The last piece of analysis we wanted to conduct on performance was whether or not being in the treatment impacted your performance on small details questions. We once again began with a simple regression analyzing the effect of being in the treatment on your score on these four questions, below are the results of this regression:

```r
reg10 <- lm(smalldetails ~ Treatment, total)
R2reg10 <- data.frame(summary(reg10)$r.squared,summary(reg10)$adj.r.squared)
colnames(R2reg10)[1]<- 'R Squared'
colnames(R2reg10)[2]<- 'Adjusted R Squared'
reg10 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                         "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	1.889	0.184	10.252	0.000
Treatment	0.490	0.256	1.915	0.061

```r
R2reg10 %>% kable(align = 'c')
```

R Squared	Adjusted R Squared
0.0636222	0.0462819

The interpretation of this regression is that those in the treatment group score .49 points better, on average, on small details questions compared to those in the control group. With a p-value of .0607, this value is statistically significant on the 90% confidence level. An R^2 of .064 does not indicate a high amount of predictive power, however, and we once again wanted to ensure that there was not omitted variable bias. Therefore, we conducted a regression of the effect of age on your score of small details. The results of that regression are:

```r
reg11 <- lm(smalldetails ~ `Age 20` + `Age 21` + `Age 22`, total)
reg11 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                         "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	3.000	0.559	5.362	0.000
‘Age 20‘	-1.000	0.669	-1.495	0.141
‘Age 21‘	-0.833	0.579	-1.439	0.156
‘Age 22‘	-1.500	0.740	-2.027	0.048

The interpretation of this regression is that, on average, 20 year olds score one point worse compared to 18 year olds on storyline questions, 21 year olds score .83 points worse compared to 18 year olds on storyline questions, and 22 year olds score 1.5 points worse compared to 18 year olds on storyline questions. With a p-value of .048, age 22 is statistically significant on the score of the small details questions. This is the same situation we had when we were analyzing the effect of treatment on overall score. The variable of age 22 is statistically significant on our x variable of treatment and on our y variable of small details. This is a case of omitted variable bias, as the effect of being aged 22 is being captured by treatment due to the fact that the treatment is statistically more likely to contain 22 year olds. To solve this omitted variable bias, we ran the following full model regression:

```r
reg12 <- lm(smalldetails ~ Treatment + `Age 20` + `Age 21` + `Age 22`, total)
R2reg12 <- data.frame(summary(reg12)$r.squared,summary(reg12)$adj.r.squared)
colnames(R2reg12)[1]<- 'R Squared'
colnames(R2reg12)[2]<- 'Adjusted R Squared'
reg12 %>% tidy() %>% kable(col.names = c("Predictor", "Coefficient", "SE", "T-Stat",
                                         "P-Value"), digits = c(0, 3, 3, 3, 3), align = 'c')
```

Predictor	Coefficient	SE	T-Stat	P-Value
(Intercept)	2.764	0.535	5.171	0.000
Treatment	0.707	0.258	2.734	0.009
‘Age 20‘	-1.269	0.638	-1.989	0.052
‘Age 21‘	-0.917	0.547	-1.677	0.100
‘Age 22‘	-1.971	0.719	-2.742	0.008

```r
R2reg12 %>% kable(align = 'c')
```

R Squared	Adjusted R Squared
0.1942222	0.131024

The interpretation of this regression is that, on average, those in the treatment group score .71 points higher on the small details questions compared to those in the treatment group holding age constant. It also states that, on average, 20 year olds score 1.27 points less than 18 year olds on small details questions compared to 18 year olds, 21 year olds score .92 points less than 18 year olds on small details questions compared to 18 year olds, and 22 year olds score 1.97 points less than 18 year olds on small details questions compared to 18 year olds. This solves the omitted variable bias problem, as we can hold age constant and analyze the effect of just being in the treatment. Once again age 22 is statistically significant, however we will not conduct further analysis on it. The new Adjusted R^2 of .131 is significantly higher than our old R^2 of .06, indicating that this model is a better predictor and does a fairly good job of predicting the variance in small details questions scored (13.1% of the variance can be explained by these variables). With a p-value of .0086, we can conclude with greater than 99% confidence that being in the treatment group has a positive impact on your scoring for small details questions.

The following table shows all of these regressions together:

```r
smalldetailsregs <- stargazer::stargazer(reg10, reg11, reg12, type = 'text',
                                title = 'Regression Results on Small Detail Score',
                                align = TRUE,
                                dep.var.labels = c('Small Detail Questions Score'),
                                no.space=TRUE)
```

```
Regression Results on Small Detail Score
==============================================================================
                                         Dependent variable:
                    ----------------------------------------------------------
                                    Small Detail Questions Score
                           (1)                (2)                  (3)
------------------------------------------------------------------------------
Treatment                0.490*                                 0.707***
                        (0.256)                                 (0.258)
`Age 20`                                    -1.000              -1.269*
                                           (0.669)              (0.638)
`Age 21`                                    -0.833              -0.917*
                                           (0.579)              (0.547)
`Age 22`                                   -1.500**            -1.971***
                                           (0.740)              (0.719)
Constant                1.889***           3.000***             2.764***
                        (0.184)            (0.559)              (0.535)
------------------------------------------------------------------------------
Observations               56                 56                   56
R2                       0.064              0.076                0.194
Adjusted R2              0.046              0.023                0.131
Residual Std. Error  0.957 (df = 54)    0.969 (df = 52)     0.914 (df = 51)
F Statistic         3.669* (df = 1; 54) 1.428 (df = 3; 52) 3.073** (df = 4; 51)
==============================================================================
Note:                                              *p<0.1; **p<0.05; ***p<0.01
```

Limitations

An ideal experiment for our study would be to have a more representative sample of college students of all different majors and from throughout the United States. Since we did not block on age and it seemed to impact our experiment, an ideal experiment would block on the undergraduate class (e.g. Freshman, Sophomore, etc.) to ensure there is a balance of education level that is representative of a real world population in both control and treatment groups.

One threat to external validity is how the study does not accurately recreate a true learning classroom environment that students experience. The study does not have motivation factors that students normally have such as impact on GPA. This could cause them to be very lighthearted in paying attention to the experiment lecture and completing the quiz. We also had one participant in the treatment group who was not able to hear the Zoom audio throughout the entire experiment. If this situation were to happen in the real world, students would figure out how to solve that problem as soon as possible to not miss the class. Since the experiment did not have any consequences, the participant did not do anything about it.

Another threat is students have different methods of learning: auditory, visual, and kinesthetic. Classroom lectures have a combination of these learning methods. Our study focused more on auditory learning based on watching a 2 minute prerecorded video on Zoom. The video length was also not representative of actual lectures which are usually an hour long. We also received feedback from participants that they wished there were captions on the lecture. Neither the control nor the treatment had captions on the video so there were no issues with inconsistent learning experiences between the groups, however we did not randomize on whether or not people preferred auditory learning and visual learning. For this reason, it is possible that one group had a larger percentage of participants that preferred auditory learning and that could have factored into it. Additionally, as stated before, we did not randomize on intelligence (for ethical reasons). The fact that our pre-experiment randomization worked on all other variables is encouraging that these two variables were randomized as well, however we could not conduct a randomization check to confirm this.

Finally, as mentioned earlier, another potential source of bias was self-selection. Participants had an option to volunteer for the experiment and thus could have created extra noise.

Conclusion

We designed an experiment to analyze the effect of having your camera on or off on performance in a learning environment. The variables we thought about in determining "performance" were the overall score people received on a quiz at the end of the experiment, how long it took them to take the quiz, and how they did on specific questions (i.e. storyline questions and small details questions). In the design of this experiment, we went through numerous steps to ensure that both groups were given the same experience with the only difference being their cameras being on or off. We had the two groups run at the exact same time, recorded a lecture video so that the material would be presented in an identical way, and made a fictional lecture so that participants could not search the answers to the quiz. In randomizing our participants, we blocked on whether they went to Boston University as well as gender, due to the gender imbalance and BU majority. Our pre-experiment randomization checks showed we randomized well, however after the experiment, we found that being 22 years old made you statistically significantly more likely to be in the treatment group - a reality we adjusted for in the regression analysis. After this experiment, we ran regressions to analyze the impact of all of these variables. We could not find a statistically significant relationship between having cameras on and overall score on the quiz, how long it took people to finish the quiz, or how people did on storyline questions. However, we can conclude with 99% certainty that having your cameras on resulted in people doing better on small details questions. Going forward, we can increase the sample size and have different colleges participate to have a more accurate experiment. We can conduct an additional experiment that further analyzes the types of questions and the effect of having your camera on or off.

Bibiliography

- Borup, Jered, West, Richard E., Graham, Charles R. (2012). Improving online social presence through asynchronous video, The Internet and Higher Education, Volume 15, Issue 3, 2012, Pages 195-203, ISSN 1096-7516, https://doi.org/10.1016/j.iheduc.2011.11.001.

- Ellis, Yvonne, Daniels, Bobbie W. and Jauregui, Andres (2010, April 24). The effect of multitasking on the grade performance of business students. Research in Higher Education Journal, Vol. 8, 2010, https://doi.org/10.1073/pnas.1611612115.

- Lepp, A., Barkley, J. E., Karpinski, A. C., & Singh, S. (2019). College Students' Multitasking Behavior in Online Versus Face-to-Face Courses. SAGE Open. https://doi.org/10.1177/2158244018824505.

- Tu, Chih-Hsiung and McIsaac, Marina (2002). The Relationship of Social Presence and Interaction in Online Classes. American Journal of Distance Education, 16:3, 131-150, DOI: 10.1207/S15389286AJDE1603_2.

- Uncapher, Melina R. and Wagner, Anthony D. (2018, October 2). Minds and brains of media multitaskers: Current findings and future directions. 115 (40) 9889-9896, https://doi.org/10.1073/pnas.1611612115.

Appendix

Figure 1: Instagram Story

ZOOM Experiment Signup

When: Sunday, November 22nd from 3PM EST to 3:15PM EST
What: Online study for 15 minutes with Wendy, Shreya, Sharon, and Lucas for our Business Analytics course
Where: ZOOM
Who: You, college undergraduate students

Further details will be sent to your email.
Thank you in advance for participating!

* Required

Email address *

Your email

What is your name? (First + Last Name) *

Your answer

What is your age? *

- 17
- 18
- 19
- 20
- 21
- 22
- 23+

What is your gender? *

- Female
- Male
- Prefer not to say
- Other:

Do you currently attend Boston University? *

- Yes
- No

Do you currently take any of your classes on Zoom? *

- Yes
- No

CAMERA: By filling out and submitting this form you are willing to have your cameras on during the study. *

- I understand

Figure 2: Experiment Signup Form

Hello,

Thank you for signing up for our Zoom experiment on this **Sunday, November 22nd at 3PM EST.**

Use this Zoom link and ***please join 2 minutes early***:
https://bostonu.zoom.us/j/95917143392?pwd=bk96UmxFRFBsQXFYQm45YUdiWm5pdz09

Meeting ID: 959 1714 3392
Passcode: 764865

Please turn your **cameras OFF before entering** and stay muted throughout the experiment.

Thank you again for your participation. All of your information will be kept confidential, however, other participants will be able to see your name during the Zoom call. If you have any questions, let us know.

Best,
Lucas, Sharon, Shreya, Wendy

Figure 3: Initial Email (Control Version)

Hello,

Thank you for signing up for our Zoom experiment on this **Sunday, November 22nd at 3PM EST.**

****UPDATE: If you are with someone else who is also participating, please join from separate rooms if possible. If not, please use headphones and do not communicate with one another.****

Use this Zoom link and ***please join 2 minutes early***:

https://bostonu.zoom.us/j/95917143392?pwd=bk96UmxFRFBsQXFYQm45YUdiWm5pdz09

Meeting ID: **959 1714 3392**

Passcode: **764865**

Please turn your cameras **OFF** before entering and stay muted throughout the experiment.

Thank you again for your participation. All of your information will be kept confidential, however, other participants will be able to see your name during the Zoom call. If you have any questions, let us know.

Best,

Lucas, Sharon, Shreya, Wendy

Figure 4: Email Sent Day-of (Control Version)

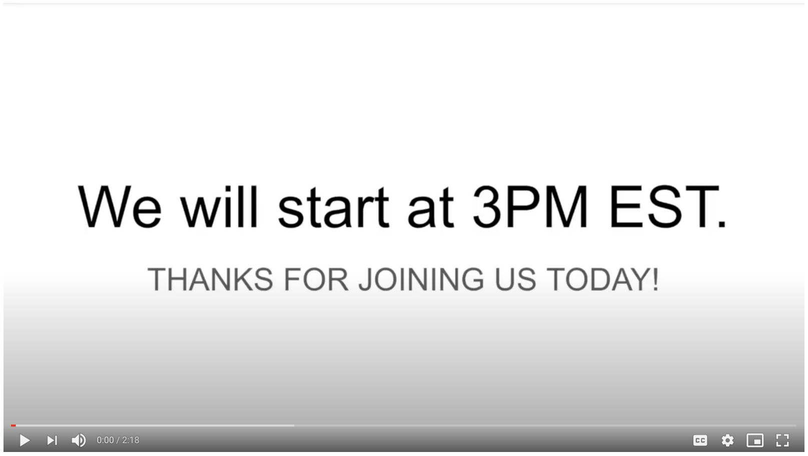

Figure 5: Lecture Video https://drive.google.com/file/d/1ZRX0bRg2RCA2uSNHwz7SD1AyNGQpYlDK/view?usp=sharing

Control
Wendy: Hi everyone, I'm Wendy!

Shreya: Hi, I'm Shreya!

Thank you for taking the time to help us with our Business Analytics class, we really appreciate you being here.

Please make sure your cameras are off and you are muted. We will start once most people are here. *MUTE YOURSELF*
[wait a minute & Wendy checks everyone is off]

DO NOT ACCEPT MORE PEOPLE INTO THE CALL AFTER 3:03PM

We will now begin the experiment, please watch the following video carefully.
MUTE YOURSELF
[play video]

Wendy: Now that you have seen this quick video, please use the Qualtrics link in the chat to answer some questions and please keep your camera off and stay muted while answering the questions.
[share link]
https://bostonu.qualtrics.com/jfe/form/SV_cPcMkrq3yiEY5Lv

After you are done with the survey, please private message me (Wendy) so I can make sure that we have received your submission before you leave. This may take a minute so please be patient and wait until you receive confirmation. Thank you again for taking the time to help us today! You can start your survey now.

Reply to participant:
Thank you, you are free to go. Happy Thanksgiving and enjoy your break!

Figure 6: Script (Control Version)