ATTENDANCE STILL MATTERS IN A WORLD OF DIGITAL LEARNING: EXAMINING STUDENTS IN BUSINESS STATISTICS

Timothy J. Haase[1]

Abstract

In this study I evaluate the importance of physically attending lectures in a business statistics course when an online digital learning companion is used. A sample of five sections of business statistics that used the exact same text, lecture format, and algorithmic assignments are used. Overall, I find that students who attend all lectures perform significantly better on exams when compared to students who have been absent. On average, students with multiple absences perform significantly worse on the online component of the course, and students who perform better on the online component tend to score significantly higher on exams.

Key Words: attendance, performance, statistics, computer

JEL Classification: A22

Introduction

College attendance and its influence on performance is not a new area of academic research. It has been nearly 100 years since Turner (1927) first explored this topic and found a negative relationship between class absences and GPA. Since then, there have been incredible technological changes that have created alternate methods for delivering courses. An article by Read (2005) highlights the use of audio recordings called podcasting at American, Purdue, Drexel, and Duke University. A similar article by Young (2008) tracks the use of video recorded lectures at the University of Minnesota-Twin Cities. Both uses of technology allow students to absorb their class lectures on their own time and on their own terms. On the other hand, others believe that in-person lectures are more effective, commonly in reference to quantitative courses. Conners et. al. (1998) and Perkins and Saris (2001) both make the case for delivering a statistics curriculum in the classroom. They cite reasons such as active learning in the classroom helping retention and mitigating anxiety, cooperative learning is available when the student is with their classmates, and the feedback from the professor being helpful. Cohn et. al. (1995) show that the individual act of taking notes during an economics lecture benefits the student more than just viewing and listening.

The purpose of this paper is to investigate the impact attendance has on student performance in business statistics when there is a technology component in addition to traditional lecture. Generation Z is becoming the new population of college student and they are very reliant on technology. How well do traditional college lectures and technology mix? Velleman and Moore (1996) and Basturk (2005), both motivating pieces, discuss the pros and cons of technology use in statistics courses, concluding that technology is a better supplement than a replacement. There are numerous ways in which the professor outperforms technology systems and I intend to see how that class time translates to student performance. In this paper I incorporate data from business

[1] Associate Professor of Economics, Anisfield School of Business, Ramapo College of New Jersey, 505 Ramapo Valley Road, Mahwah, NJ 07430

statistics courses during three semesters from 2018 to 2019. The classes were taught traditionally with face-to-face lectures and incorporated an online learning component comprised of assignments, tutorials, study materials, and a statistical spreadsheet application. In this study I estimate the value attendance has on online assignment performance and on in-class exams while controlling for the online learning component. A brief literature review follows, which outlines the background motivation. I present the data next, followed by a discussion of the methodology and results. I conclude with a summary of the results, implications for teaching, and extensions to consider.

Background

There is a large collection of literature that focuses on the importance of attendance in varying fields. Anikeef (1954) estimated that 83% of class grade variation in a business school is explained through absences and other factors. Day (1994) determined that absences were more important than GPA in predicting test scores in sociology classes. Gump (2005) found a strong negative relationship between absences and final grades in an Introduction to Japanese Culture general education course with no difference between the student majors that were represented. Newman-Ford et. al. (2008) found a significant and strong relationship between attendance and assessment outcomes for four different degree programs at the University of Glamorgan that utilized electronic attendance monitoring. A more comprehensive meta-analysis was done by Credé et. al. (2010) determining that class attendance is the best-known predictor of academic achievement.

Psychology is one of the fields of study where research seems to concentrate. Gunn (1993), Van Blerkom (1992, 1996), and Clump et. al. (2003) all find a negative relationship between absences and student performance for different undergraduate psychology courses. Buckalew et. al. (1986) interestingly found that being absent from the first class meeting had a negative impact on performance in five different psychology courses. They also noted that seating arrangement mattered – students seated closer to the front of the classroom performed better. Launius (1997) also finds that higher attendance leads to higher exam scores as well as performance in outside assignments.

Different fields of science have also been investigated. Moore (2006) determined that attendance is a strong correlate of success for first year students in biology. Moore et. al. (2003) found very high correlations between attendance and performance in freshmen level introductory science. They further note that attendance increased and so did grades when the correlation between attendance and grade was presented to the class. The authors determined that weekly reminders were effective to freshmen, especially when a class has no mandatory attendance policy. Jenne (1973) found a strong relationship between attendance and learning in health science. The author referred to attendance as “distributed practice.” However, Murphy and Stewart (2015) found attendance in physics courses had no real effect when lectures were replaced with recordings. They considered face-to-face lectures and recorded lectures. Those that chose recordings over attending lectures were lower achievers prior to the choice. The substitution of lectures with the virtual medium benefited the lower achieving student, but not enough to return them to the class average.

Economics is another area with a sizeable collection of studies. Brocato (1989), Park and Kerr (1990), Durden and Ellis (1995), Cohn et. al. (1995), Devadoss and Foltz (1996), Maloney and Lally (1998), Marburger (2001), and Chen and Lin (2008) all produced variations of absenteeism negatively affecting student performance. Romer (1993) used data from intermediate macroeconomics to test the link between attendance and exam scores. He also incorporated controls for motivation such as GPA and fraction of assignments completed. He determined that attendance has a significant influence on exam scores and that the controls for student motivation (GPA, fraction of assignments completed) only have a moderate impact on that influence. Cohn and Johnson (2006), another motivating work, analyze students from principles of economics classes. They test numerous hypotheses from Jones (1984), Durden and Ellis (1995), and Romer (1993). The authors find that attendance has a positive influence on test scores; substantial absences have a larger negative impact on test scores; low test scores do not cause more absences; and that SAT and GPA controls have more explanatory power than previously thought. Uniquely, they incorporate dummy variables to categorize students by different percentages of classes attended.

Boyle and Goffe (2018) used two large sections of a principles of macroeconomics course to apply research-based teaching methods. These methods were identified by cognitive scientists in the STEM fields and provide evidence as to why attendance matters. The authors incorporate numerous teaching methods with success. Their sample of over 500 students produced significant learning increases on the Test of Understanding of College Economics. The four notable teaching methods identified as having the most impact are: providing considerable feedback; spacing of learning; frequent use of clickers to quiz on conceptual understanding; and quiz reflections.

Some literature using statistics courses focus on the use of technology in the classroom. Velleman and Moore (1996) illustrate many of the pros and cons of incorporating multimedia into the classroom. This referred to computer-based systems that combined sight, sound, and interaction from the student. The authors praise computers due to the large impact they make in teaching statistics however note it supplements teaching – not replace. Their arguments are similar to Conners et. al. (1998) and Perkins and Saris (2001) by claiming students benefit more from their own activity. They do however state that new technology is capable of successfully replacing teachers if the student is mature, strongly motivated, and disciplined. For most introductory statistics courses, this would not be the case. Basturk (2005) used CAI (Computer Assisted Instruction) with graduate students in an introductory statistics course at Carnegie I Research University. Roughly one third of the 205 students in the study signed up for a "lecture-plus-CAI" section where they would complete computerized exercises and tutorials in addition to the regular lecture. Students who completed the CAI section scored significantly higher on both midterms and finals when compared to the lecture only cohort.

Data Collection and Variable Summary

The student data I use comes from five different course sections of a business statistics course I have taught from spring 2018 through spring 2019. The student population is typically sophomores and juniors in the business school; this course is a core course for all majors and requires a prerequisite math course. Each section had the same instructor, textbook, lecture format, number of exams, and exam format. Each section also utilized Pearson's MyStatLab, an online "digital learning environment," for assignments, tutorials, study material, and spreadsheet applications. The students also spend one class in a computer lab for instruction on Microsoft Excel, after which tutorials and assignments are made available.

The lectures meet twice a week for 100 minutes each session and have a class capacity of 35 students. The frequent amount of interaction provides opportunities to connect statistical methods to practical, real world examples. Most importantly, the rapport built in a small classroom allows the instructor to better know the students and thus be more aware of confusion in the classroom. These lectures incorporate the social learning, curse of knowledge, considerable feedback, strengthening of schema and deliberate practice teaching methods outlined by Boyle and Goffe (2018). Each lecture has time where the students are able to work through a question about that days' topic. This creates two opportunities: students are able to work with each other and help each other out, and I am able to talk with students who are struggling. Both of these interactions are things Velleman and Moore (1996) describe to be a weakness to technology use outside the classroom.

Technology is incorporated into the lectures using Microsoft Excel and MyStatLab to better solve or display data. Attendance is also taken during this time. There is no formal attendance policy, and a grade is not assigned to attendance. Students are warned in the beginning of the semester that missing class will result in a lot of missed material. I do not provide notes; should someone miss class they must rely on classmates. Since attendance is not for a grade, I do not distinguish between excused or unexcused. The focus is solely on who was present for the lecture. After accounting for exams, finals week, computer lab days, and snow days, there are 22 face-to-face lectures for each of the courses. I follow Brocato (1989) and Gump (2005) by not including the first day of the semester.

Student's assignments, textbook, and study materials are all online in MyStatLab. The homework assignments are designed using algorithm-built questions so no two students receive the exact same question. Each student will work through the same type of question and calculate the same statistics, but the sample data randomly changes between individuals in an effort to minimize cheating. There are numerous learning tools within the program as well. There are video tutorials and presentations, self-assessment quizzes, an online text that links homework questions to textbook chapter and section, step-by-step walkthroughs for calculating complicated formulas, and more. At the end of the semester I can export a spreadsheet outlining student performance and time spent on each assignment. I do adjust homework settings so students have 3 attempts per assignment and the best performance is kept for their grade. This provides students the opportunity to try their hand at working through problem sets without worrying of getting them wrong the first time. It also allows for the motivated to try again to increase their scores. Anecdotally, I have seen class exam score averages increase from using this program.

After accounting for withdrawals and incomplete students, I have a total of 169 students that completed the course. The sample of data was gathered after the semesters had ended so I am limited to performance measures that a professor normally can observe. Table 1 shows a simple summary of absences by letter grade earned. Comparisons of the extremes suggest a distinct pattern between students that earn either an A or A- and F. In fact, the group of students that scored in the A-range had a lower average number of absences and median number of absences than all other grade levels. With exception of the transition from the C-range to the D-range, the average and median number of absences increases as letter grade worsens.

Table 1: Summary of Absences by Letter Grade Earned

Grade Range	Students	Absences			
		Average	Median	Min	Max
A	47	1	0	0	5
B	45	1.489	1	0	5
C	34	3.353	2	0	18
D	28	2.107	2	0	8
F	15	4.667	3	1	12
Whole Sample	169	2.112	1	0	18

To investigate the role attendance has on student performance, I gathered or calculated the following variables:[2]

- ***Test***: weighted average of all exams. Each student has two midterms and a final exam. Each exam covers the same course material and is objective in nature. Value range is from 0 – 100.
- ***Labscore***: homework assignment score from MyStatLab. It is an average of all chapter assignments. Value range is from 0 – 100.
- ***Labpercent: Labscore*** but in decimal form. For interpretation of coefficients in regressions.
- ***Labhr***: total number of hours spent on assignments in MyStatLab. Fractional hours are allowed.
- ***Fraction***: fraction of homework assignments completed. Value range is 0 – 1.
- ***Att***: attendance as a fraction of lectures attended. Value range is 0 – 1.
- ***Abs0***: dummy variable for students with no absences. 33.73% of students are represented.
- ***Abs1***: dummy variable for students with one absence. 17.16% of students are represented.
- ***Abs2***: dummy variable for students with two absences. 23.08% of students are represented.
- ***Abs3plus***: dummy variable for students with three or more absences. 26.04% of students are represented.
- ***Fall18 & Spring19***: dummy variables to capture semester fixed effects. The spring 2018 semester is the reference group.

Test and ***Labscore*** are the two performance measures of concern. Table 2 and Table 3 display summary measures for ***Test*** and ***Labscore***, respectively, with different combinations of attendance percentages and assignment completeness.

Upon inspection of Table 2, it is evident that students who attend every class and complete all assignments perform the best on exams. Students who do not complete all assignments perform the worst. This is irrelevant of attendance. Also students who attend all classes perform better than those that have absences, and students that complete all assignments perform better than those who missed at least one. The comparison to take from Table 3 is that students who attend all classes have a higher average assignment score on MyStatLab that students with absences.

[2] This project was approved by the Ramapo College Institutional Review Board (IRB Approval #489)

Table 2: Test Summary Statistics

		Obs.	Mean	Std. Deviation	Min	Max
Full Sample		169	77.589	14.216	34.67	98.89
Attendance	***=100%***	57	84.259	12.263	56.67	98.89
	<100%	112	74.191	13.976	34.67	98.89
Assignments	***=100%***	142	79.675	13.748	34.67	98.89
	<100%	27	66.603	11.442	43.2	91.33
Subgroups						
Attendance = 100% and Assignments = 100%		53	85.631	11.573	56.67	98.89
Attendance = 100% and Assignments < 100%		4	66.081	3.394	63.22	70.13
Attendance < 100% and Assignments = 100%		89	76.129	13.771	34.67	98.89
Attendance < 100% and Assignments < 100%		23	66.693	12.373	43.2	91.33

Table 3: Labscore Summary Statistics

		Obs.	Mean	Std. Deviation	Min	Max
Full Sample		169	85.478	18.022	10	100
Attendance	***=100%***	57	94.267	9.662	46.206	100
	<100%	112	81.004	19.612	10	100

Methodology and Empirical Results

The first two equations I regress follows the model established by Romer (1993). I use these as a benchmark to check the relationship between attendance and performance.

(1) $Test_i = \beta_0 + \beta_1 Att_i + \beta_2 Fall18_i + \beta_3 Spring19_i + \varepsilon_i$
(2) $Test_i = \beta_0 + \beta_1 Att_i + \beta_2 Fraction_i + \beta_3 Fall18_i + \beta_4 Spring19_i + \varepsilon_i$

Equation 1 tests determines the impact attendance has on exam scores when measured in a continuous nature. Equation 2 includes the fraction of assignments completed to capture a proxy for motivation. All equations include semester dummy variables to control for semester-effects. Table 4 displays the results.

Table 4: Benchmark Test Regressions

Independent Variable	**(1)**	**(2)**
Intercept	58.344***	46.996***
	(8.281)	(9.966)
Att	27.365***	21.097**
	(8.690)	(9.160)
Fraction	-	17.418**
		(8.679)
Fall18	-6.232**	-5.695**
	(2.835)	(2.822)
Spring19	-7.790***	-7.575***
	(2.839)	(2.826)
Observations	169	169
R-squared	0.102	0.123
Adj. R-Squared	0.085	0.102
F-Statistic	6.22	5.76
*,**,*** indicates significance at the 10%, 5%, and 1% levels		
Standard errors in parentheses		

The coefficient of 27.365 for ***Att*** in equation 1 represents the increase to exam scores when going from no attendance to attending 100% of classes. ***Att*** is measured as a fraction, so a student who only attends half the classes tends to score 13.6 points lower than a student with full attendance. It is statistically significant at the 1% level. Romer (1993) estimated that students who attended 100% of the lectures earned a B+. These results are similar, estimating that a student with 100% attendance would earn 85.7 points on a 100-point scale, which is a B. Including ***Fraction*** in equation 2 adds some explanatory power but ***Att*** remains significant. Romer (1993) noted that including the fraction of problem sets completed as a proxy for motivation did not negate the importance of attendance. His estimated coefficient for attendance remained significant but decreased by 20.5%. In my sample, the coefficient on ***Att*** decreases similarly by 22.9% and is significant at the 5% level. Now, a student who attends all classes will on average score 21.097 points higher on exams compared to the previous 27.365. These results are in line with Romer (1993), that even with a proxy for motivation, attendance is still a stronger indicator of increased performance. The dummy variables ***Fall18*** and ***Spring19*** are both significant, negative, and close in magnitude. When compared to the reference semester Spring 2018, students in the 2018-2019 academic year performed between 6.232 - 7.79 points lower on the overall exam score in equation 1. The decrease in exam scores lessens in equation 2 to a range of 5.695 – 7.575 points.

The remaining equations I estimate follow a structure motivated by Cohn and Johnson (2006). They incorporate discrete dummy variables indicating different levels of absences with their students to test the conclusion of Durden and Ellis (1995) that substantial absences have a detrimental impact on performance. The attendance dummy variables used by Cohn and Johnson

(2006) are based on different percentages attended. For example, their sample had 8% of students attended all classes, 28% of students attended 92% or more but less than 100% of classes, and 23% of students attended less than 68% of classes. My sample has a very different pattern, so using these types of percentages does not represent it well. I use four dummy variables to represent the number of absences: no absences (33.73% of sample); one absence (17.16% of sample); two absences (23.08% of sample); three or more absences (26.04% of sample). Considering that the attendance data I have constitutes 22 class meetings, missing two, or three or more could be considered substantial. Since the course meets twice a week, missing two classes is the equivalent of missing one full week. Equation 3 represents the regression using the dummy variables for absences to estimate test scores. The dummy that is omitted is the indicator for zero absences.

$$(3)\ Test_i = \beta_0 + \beta_1 Abs1_i + \beta_2 Abs2_i + \beta_3 Abs3plus_i + \beta_4 Fall18_i + \beta_5 Spring19_i + \varepsilon_i$$

I also estimate variants that include the variables for the online digital learning component. This is motivated by Basturk (2005) who shows students that participated in "computer assisted learning" performed better on exams. Equation 4 incorporates the amount of time a student spent in MyStatLab and equation 5 includes their performance measured as a decimal.

$$(4)\ Test_i = \beta_0 + \beta_1 Abs1_i + \beta_2 Abs2_i + \beta_3 Abs3plus_i + \beta_4 Labhr_i + \beta_5 Fall18_i + \beta_6 Spring19_i + \varepsilon_i$$

$$(5)\ Test_i = \beta_0 + \beta_1 Abs1_i + \beta_2 Abs2_i + \beta_3 Abs3plus_i + \beta_4 Labpercent_i + \beta_5 Fall18_i + \beta_6 Spring19_i + \varepsilon_i$$

I further examine the value of attendance by regressing the same variables from equations 3 and 4 on ***Labscore*** as an alternative performance measure. I believe students' performance on the online assignments will benefit from in class attendance, even considering all the relevant material, explanations, and tutorials are present in the online program. Equations 6 and 7 represent those two specifications. All equations include semester dummy variables to control for semester-effects. Table 5 displays the results.

$$(6)\ Labscore_i = \beta_0 + \beta_1 Abs1_i + \beta_2 Abs2_i + \beta_3 Abs3plus_i + \beta_4 Fall18_i + \beta_5 Spring19_i + \varepsilon_i$$

$$(7)\ Labscore_i = \beta_0 + \beta_1 Abs1_i + \beta_2 Abs2_i + \beta_3 Abs3plus_i + \beta_4 Labhr_i + \beta_5 Fall18_i + \beta_6 Spring19_i + \varepsilon_i$$

The coefficients from equation 3 capture the impact of different amounts of absences. The omitted dummy is for no absences, so all coefficients are interpreted as the change in ***Test*** for an increase in absences from zero. The coefficient on ***Abs1*** is -7.440 and is significant at the 5% level. This indicates that the average student who misses one class will score 7 points lower on their exams. The coefficient on ***Abs2*** is -11.455 and is significant at the 1% level, indicating a larger drop in test scores for missing two classes. The coefficient of -10.253 for ***Abs3plus*** is smaller in magnitude than ***Abs2*** indicating a smaller loss in test scores for missing three or more classes over the semester. It is also significant at the 1% level. This specification has a higher goodness of fit compared to the benchmark specification in equation 1 and the F-statistic is significant as well.

This equation is closest to the specification tested by Cohn and Johnson (2006). They found that students who attended between 76 – 84% of classes lost about 5 points to their weighted average exam score, and students that attended less than 68% of class meetings lost about 6 points from their scores. I am able to provide similar evidence that absences correlate to lower exam scores, albeit in greater magnitude.

Table 5: Regression Results

Independent Variable	Test			Labscore	
	(3)	(4)	(5)	(6)	(7)
Intercept	89.800*** (2.653)	96.475*** (2.935)	53.107*** (5.942)	97.448*** (3.292)	92.835*** (3.790)
Abs1	-7.440** (3.032)	-7.243** (2.874)	-5.687** (2.701)	-4.654 (3.761)	-4.790 (3.710)
Abs2	-11.455*** (2.767)	-12.041*** (2.626)	-6.542** (2.560)	-13.045*** (3.433)	-12.640*** (3.390)
Abs3plus	-10.253*** (2.653)	-10.665*** (2.516)	-3.475 (2.559)	-17.999*** (3.291)	-17.714*** (3.248)
LabHR	-	-0.289*** (0.065)	-	-	0.199** (0.084)
Labpercent	-	-	37.654*** (5.599)	-	-
Fall18	-6.620** (2.790)	-5.347** (2.660)	-5.826** (2.477)	-2.109 (3.462)	-2.989 (3.434)
Spring19	-7.566*** (2.757)	-7.114*** (2.615)	-5.060** (2.474)	-6.656* (3.421)	-6.969** (3.376)
Observations	169	169	169	169	169
R-squared	0.165	0.254	0.347	0.201	0.227
Adj. R-Squared	0.139	0.227	0.323	0.176	0.199
F-Statistic	6.43	9.21	14.35	8.18	7.93

*,**,*** indicates significance at the 10%, 5%, and 1% levels
Standard errors in parentheses

Equation 4 includes the variable ***Labhr*** to control for effort by the student. The coefficients on ***Abs1***, ***Abs2***, and ***Abs3plus*** all remain significant at the same levels. The magnitudes for each change very little, and the coefficient for ***Abs3plus*** remains smaller in magnitude than ***Abs2.*** The coefficient on ***Labhr,*** oddly enough, is negative with a value of -0.289 and is significant at the 1% level. The interpretation that spending more time working through exercises in MyStatLab having a negative effect on test scores could imply that there are a number of students who really struggled and spent a long time on assignments. This mode of assessment with much more relaxed time requirements may not translate well to timed exams for some. The goodness of fit for this specification increased with an adjusted R-squared of 0.227 and the F-statistic is significant.

Using ***Labpercent*** as the measure of student ability in equation 5 instead of the time spent working in the online digital learning environment creates dramatic changes in the coefficients. The coefficient for the intercept decreases almost in half to 53.107 and is significant at the 1% level. The coefficients on ***Abs1*** and ***Abs2*** are significant at the 5% level. Having three or more absences now is no longer a significant predictor of test scores. Students absent once have test scores 5.687 points lower than those always in attendance; students who miss two class have scores 6.542 points lower. The coefficient on ***Labpercent*** is significant at the 1% level and has a value of 37.654. This variable is measured as a percent between 0 and 1 so a student who earned a 100% on their MyStatLab assignments increases their test scores, on average, by 37.654 points. This specification has the largest adjusted R-squared of 0.323 and F-statistic of 14.35.

The results for equation 6 produce coefficients that further make the case for attending class – more specifically, not missing too many. The coefficient for ***Abs1*** is not significant indicating that missing one class has a negligible effect on your online assignment score. ***Abs2*** and ***Abs3plus*** are both negative and significant at the 1% level. Students who miss two classes have lower online assignment score by an average of 13.045 points; those that miss three classes or more have online assignment scores that are 17.999 points lower than those that make it to every class. This specification has an adjusted R-squared of 0.176. Including ***Labhr*** in equation 7, although significant at the 5% level, does very little to the magnitude of the other coefficients discussed and slightly increases the adjusted R-squared to 0.199. The coefficient of 0.199 for ***Labhr*** logically implies that spending more time working on the online assignments will yield a higher score.

At this point, we can look at the results from equations 5 and 7 together. From equation 5, we can confidently say that there is a significant correlation between a student's test score and that student's performance in their online assignments, and whether or not they missed one or two classes. Perhaps there is some small detail missed from class that an exam covers, or perhaps the exercise worked on in class had a large learning benefit for those in attendance. But why do larger absences not matter in the test regressions? Equation 7 illustrates that two absences has a large negative impact on the online assignment score. Three or more absences has an even larger negative impact on the online assignment score – equal to the different between a B- and F. I think this is a unique impact because students have more time and multiple attempts to perform well on these assignments. The adverse effects of missing too many classes is most amplified in the online performance regressions, which in turn has the largest coefficient in any exam scores regression.

An important limitation worth noting is that these equations lack some standard indicators of ability. Romer (1993) and Cohn and Johnson (2006) both incorporated SAT scores and GPA. These variables, when included, lessen the magnitude of attendance coefficients although attendance maintains its significance. I did not include these variables due to timing – this study was constructed after the semesters had ended and distributing letters of intent was inefficient. I do not have any reason to believe that these variables would have altered the story of how attendance is a good estimator of performance. However, gathering this information for future semesters would be very insightful for explaining more of the variation in performance and create more accurate representation of the role of attendance.

Conclusion

There are numerous studies in academic literature that estimate the effect of attendance on college performance. The overall sense is that attending class has significant benefits to the student. Boyle and Goffe (2018) outlined many teaching methods that benefits the in-person classroom, and many of these methods were applied. Historically, many other studies date back decades and do not necessarily incorporate all of the available technologies available to student and professor alike. Generation Z, the current student population, is incredibly technology reliant. This study explains how both traditional lecture and the use of online digital learning environments can both benefit the student and are intertwined.

I focused on students from a sophomore/junior level business statistics course and collected grade data as well as attendance. I find that physically showing up to class still has strong benefits to the student. Students who attend class regularly perform better on exams. Students who are regularly absent perform worse on exams and perform much worse on their online assignments. Not surprisingly, students who perform better on their online assignments also perform much better on exams. The conclusions to be taken from this study is that attendance is important for student performance, both on exams and on their assignments. Performance on their assignments, particularly when facilitated through an online digital learning environment full of supplemental help, is a very strong predictor of success on exams. The notion by Velleman and Moore (1996) that technology in the classroom is a great supplement, not a replacement, for lectures and the findings of Basturk (2005) that students perform better in statistics if they work with computers are supported with this study.

The scope of this study is limited to the data, which was gathered after the semesters had ended. Therefore, drafting letters of consent and applying for a more in-depth study with the Institutional Review Board was not possible. Going forward, I would plan to extend this study incorporating more traditional metrics of ability (e.g.: GPA, credits taken, SAT, what math prerequisite was taken, grade earned in prerequisite). Additionally, it would be a proper experiment to use data from hybrid courses, traditional courses, and online courses.

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