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Class Participation and Student Performance: A Follow-up Study

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Abstract

Student attendance in class, and participation while in class, are predictors of student performance. Last year, we reported on a new measure combining class attendance and attentiveness while in class and used this participation score as a predictor of student performance on the final exam in the class. This year, we follow up by analyzing data for four classes in the Fall semester of 2019. In each class, and for the four classes combined, we found a statistically significant relationship between participation and score on the final exam.
Keywords: participation, attendance, attentiveness, distraction, student performance

1. INTRODUCTION

Traditionally, education has taken place in face-to-face environments. The advent of distance education started in the 19th century with correspondence courses, followed by television-based courses in the mid-20th century, but the real growth of distance education occurred with the development of the Internet in the late 20th and early 21st century (Visual Academy, 2020). The Internet enabled three forms of interactivity: interaction with content, with the instructor, and with other learners (Craig, 2020). Class participation is becoming more important than pure class attendance alone (Büchele, 2020).

When most classes were still taught face to face, participation was measured in terms of coming to class (attendance). Romer (1993) advocated mandatory attendance based on the strong relationship between attendance and performance. Other researchers examined the usefulness of different participatory metrics (hand raising, response cards, clickers). In the Internet environment, measures of attendance focused on time spent on the course site, clicks, and pages visited. Participation shifted to making meaningful contributions in email conversations and on discussion boards. In general, research shows that active class participation improves subjective and objective student performance. Students perceive that they do better in class, and objective criteria like Grade Point Average (Credé, Roch, & Kieszczynky, 2010) and scores on final exams confirm this (Duncan, Kenworthy, Mcnamara, & Kenworthy, 2012; Irwin, Burnett, & McCarron, 2018).

Over the last twenty years the possibilities for virtual delivery have blossomed as networks have greatly improved in speed, stability, and ease of connectivity. In 1998, dial-up internet was still limited to 56Kbps and connections had to be set up for each session. Broadband started to replace dial-up in the early 2000s and provided always-on connections in the Mbps range. Currently, fiber-optic broadband provides speeds in the Gigabit range. Additionally, users are no longer limited to wired connections. Wireless connections are now fast enough to be useful in education, and content management systems like Blackboard are optimized for use on mobile devices. A variety of class formats has emerged based on the different combinations of time and place.

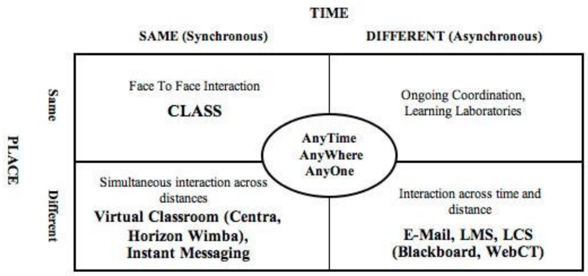

Figure 1- Course Delivery Formats (Daniels & Pethel, 2014)

Using different combinations of time and place depicted in Figure 1, our regional university in the Southwest offers face to face courses (same place, synchronous), Interactive Videoconferencing and Virtual Class Meetings (different place, synchronous), fully online courses over Blackboard (different place, asynchronous), and blended courses delivered partly face to face and partly asynchronously over Blackboard (Northeastern State University, 2019). Using videoconferencing software is useful in the traditional classroom too. Presentation tools include traditional blackboards, whiteboards, digital whiteboards, overhead projectors, ceiling-mounted classroom projectors, and computer lab monitors. These are not easily visible to all students in the classroom. Using the Equivalent Visibility Rule, students in the back of the class are better off using individual computer screens (Feierman, 2020). When teaching in computer labs, using videoconferencing software is therefore a good alternative over projection to a screen in front of the class. Offering multiple modes of attending may increase attendance for students who might otherwise miss class for employment reasons (Lukkarinen, Koivukangas, & Seppala, 2016; Paisey & Paisey, 2004), while simultaneously meeting the preferences of those who prefer real-life lectures over web-based lecture technologies (Gysbers, Johnston, Hancock, & Denyer, 2011). Francescucci and Rohani (2019) compared face to face and virtual classes for the same Marketing course and found no differences in outcomes between them.

This paper builds on previous research (Bekkering & Ward, 2019), where we compared two classes. We used videoconferencing to stream the instructor desktop to the lab computers and used the interactive tools to communicate electronically. In a lecture-oriented class, we found a significant relationship between class participation and scores on final exams. In the skills-based programming class, the lecture component was not a determinant but attendance in the associated labs was. In the classes used for this study, like before, we used data in the professional version of our videoconferencing software to objectively measure student participation as the product of attendance (coming to class) and attentiveness (paying attention while in class). Student performance was again measured by the score on comprehensive final exams, and the results analyzed for four courses in the 2019 Fall semester separately and collectively. The contribution of this research is the use of a single measure of class participation, without interpretation by the researchers.

2. LITERATURE REVIEW

The research literature has supported that class attendance improves student performance (Coldwell, Craig, Paterson, & Mustard, 2008; Landin & Pérez, 2015; Teixeira, 2016; Yakovlev & Kinney, 2008; Landin & Pérez, 2015; Zorio-Grima & Merello, 2020). It is considered a better student success predictor than SAT, high school GPA, study habits, study skills (Credé et al., 2010), self-financing, and hours worked (Devadoss & Foltz, 1996). The effect may not be completely linear. Durden & Ellis (1995) found that students could miss up to four classes without negative effect.

Beyond attendance, active participation makes a difference, in both synchronous and asynchronous conditions (Duncan et al., 2012; Nieuwoudt, 2020). Mean course grades are higher for students who actively engage in discourse than those who just do the work(Beaudoin, 2002).

New communication technologies have had positive and negative effects on participation. Some technologies, like social media, are used for class purposes (Kraushaar & Novak, 2010). Whether this helps or hinders students, depends on how they are used. Using Facebook for class may have a positive effect, while using it for socializing may be negative (Junco, 2012a). Overall, using social media for class purposes may not be effective (Lau, 2017).

Whether students attend locally or remotely may not matter (much). Meta-analysis for asynchronous education showed slightly better student performance in distance education

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courses (Allen, Mabry, Mattrey, Bourhis, Titsworth, & Burrell, 2004) , but synchronous education may be equivalent to the physical classroom (Mullen, 2020). With a wide variation in effect, positives may cancel out negatives especially when students have additional tasks to perform (Bernard, Abrami, Lu, Borkhovski, Wade, Wozney, Wallet, Fiset, & Huang, 2004). When the task load is identical, for local and distant students in a videoconferencing setting, student performance is the same (MacLaughlin, Supernaw, & Howard, 2004). Interaction may make the difference: distance education with collaborative discussions is more effective than independent study only (Lou, Bernard, & Abrami, 2006). Just recording lectures and posting notes online may not meet students' needs (Gysbers et al., 2011). For synchronous online session, special attention tracking tools may be available. Zoom had an attention tracking feature until April 2020, when it was removed for security and privacy reasons (Yuan, 2020). Cisco Webex still provides group and individual attentiveness indicators and participant attention reports (Cisco Webex, 2018)

Class Participation

Active participation in class can take multiple forms. In face to face classes, participation can mean the use of response cards and hand-raising (Christle & Schuster, 2003; Gardner, Heward, & Grossi, 1994; Narayan, Heward, Gardner, Courson, & Omness, 1990). Sometimes, special tools like clickers were used (Stowell & Nelson, 2007), but also cellphones for text messaging (Nkhoma, Thomas, Nkhoma, Sriratanaviriyaku, Truong, & Vo, 2018; L.-C. C. Wang & Morgan, 2008). In the online environment, the initial measurement of participation in asynchronous classes might be with pages visited, tools used, messages accessed, discussions posted, and email contacts (Coldwell et al., 2008; Douglas & Alemanne, 2007; Romero, Lopez, Luna, & Ventura, 2013). Some novel tools like location and Bluetooth data have been used (Kassarnig, Bjerre-Nielsen, Mones, Lehmann, & Lassen, 2017), as has spyware installed on student laptops to check browsing and application use (Kraushaar & Novak, 2010), but these are more for research and not for day-to-day teaching.

In the digital environment, all modern Learning Management Systems (LMS) provide some form of videoconferencing to enable virtual class meetings. Moodle has a Videoconference Edition (Moodle, Inc., 2019). Blackboard offers the Blackboard Collaborate module (BlackBoard Inc, 2019). Canvas includes the Conferences tool (Canvas LMS Community, 2019). Zoom is not an LMS, but it is often used in education and can be integrated in Blackboard, Moodle, and other platforms.

Modern videoconferencing software provide multiple interaction tools. Some of them are based on their physical counterparts, such as voice communication and virtual hand raising. Information can be shared through programs such as PowerPoint, sharing of the presenter's desktop, whiteboards, slideshows, and sharing of online videos. Collaboration tools include chat messages, annotation and drawing tools on shared desktops, and transfer of control over mouse and keyboard. These tools transform the shared view into two-way communication between instructor and students (SJSU, 2018)

Finally, some forms of interaction scale better than others. Multiple choice quizzes work well for any size audience, but voice discussions are best limited to small groups (Garner, 2018).

Student Performance

Once we assume that class attendance and class participation influence how well students do in class, we need to select a way to measure their performance. Multiple metrics have been used to measure student performance. Most frequently used are readily-available items like course grades (Beaudoin, 2002; Durden & Ellis, 1995; Kassarnig et al., 2017; Teixeira, 2016), term GPA (Wang, Harari, Hao, Zhou, & Campbell., 2015), cumulative GPA (Lau, 2017), self-reported GPA (Kirschner & Karpinski, 2010), GPA obtained from registrars (Junco, 2012a), course credits (Giunchiglia, Zeni, Gobbi, Bignotti, & Bison, 2018), scores on final exams (Duncan et al., 2012; Lukkarinen et al., 2016) and finishing the course (Coldwell et al., 2008; Junco, 2012b). Occasionally, pre-tests and post-tests (Omar, Bhutta, & Kalulu, 2009), student ranking (Felisoni & Godoi, 2018) or multi-item scales are used (Yu, Tian, Vogel, & Chi-Wai Kwok, 2010).

On the other hand, a significant number of studies rely on self-report by students (Junco & Cotten, 2011), including self-report of GPA and hours spent studying (Kirschner & Karpinski, 2010). However, some caution must be used since self-report may not be as reliable (Kuncel, Crede, & Thomas, 2005)

Multitasking

Using computers, cell phones, and other technology does present new problems. McCoy (2016) reported that students used digital devices 11.43 times per school day. More than 25% of effective class time may be spent on the phone (Kim, Kim, Kim, Kim, Han, Lee, Mark, & Lee, 2019). Students often alternate between class-related and non-class-related computer use (Fried, 2008; Grace-Martin & Gay, 2001; Hembrooke & Gay, 2003; Janchenko, Rodi, & Donohoe, 2018). Cell phone use among college students is becoming an addiction (Roberts, Yaya, & Manolis, 2014).

Multitasking in class has evolved with the technology of the day. When laptops entered the classroom, instant messaging and web browsing were major distractions (Fox, Rosen, & Crawford, 2009; Hembrooke & Gay, 2003). Later, Facebook became a major distractor (Kirschner & Karpinski, 2010). Now, mobile phones provide yet another source of distraction (Chen & Yan, 2016; Harman & Sato, 2011). Cell phone applications include WhatsApp (Ahad & Lim, 2014), Snapchat and Instagram (Griffin, 2014). The negative effect of using cellphones is especially high when it takes place in class (Felisoni & Godoi, 2018), and lower performing students are especially at risk (Beland & Murphy, 2016; Chiang & Sumell, 2019). Beland and Murphy (2016) also found significant improvement in high stakes exam scores after mobile phones were banned.

Multitasking with technology negatively affects participation and student performance, subjectively (Junco & Cotten, 2011) and objectively (Amez, Vujic, De Marex, & Baert, 2020b; Amez & Baert, January 1, 2020a; Junco & Cotten, 2012; Kates, Wu, & Coryn, 2018). Students do not necessarily recognize the negative effect. In a study of Malaysian university students, respondents felt that they performed better as Facebook usage increased (Ainin, Naqshbandi,Moghavvemi, & Jaafar, 2015).
The general research consensus holds that multitasking does have a negative effect on student performance (Bellur, Nowak, & Hull, 2015; Burak, 2012; Junco & Cotten, 2012; Kraushaar & Novak, 2010; Kuznekoff, Munz, & Titsworth, 2015; MacLaughlin et al., 2004), although the causality has not yet been established (van der Schuur, Baumgartner, Sumter, & Valkenburg, 2015). Controlled experiments show that actual performance may be the same, but the time to achieve it is longer (Bowman, Levine, Waite, & Genfron, 2010; Rubinstein, Meyer, & Evans, 2001). While some studies fail to demonstrate differences between performance of cognitive tasks with and without distraction, they do show decreased efficiency of information processing (End, Worthman, Mathews,& Wetterau, 2010) and increased memory errors (Rubinstein et al., 2001).

3. METHODOLOGY

Data for the four classes in this study were automatically recorded by the videoconferencing software. Data points were join time, leave time, and attentiveness score for each student in each course. Students were allowed to enter the class before it started, and before the instructor. If students entered early, the official start time of the class was used. The instructor used the full class period and closed the session after the class was officially over. If students left after the class was officially over, the official closing time was used. Network interruptions or equipment problems occasionally dropped students from the session, and they could immediately rejoin the class without instructor intervention. The attentiveness score reflected the percentage of time that the focus of the student's computer was on the desktop shared by the instructor. The syllabus explained the attentiveness statistic and instructed the students to maximize the class window to avoid accidental low scores. All lectures were recorded and generally available online after two hours and use of pen and paper for notes was suggested. Students had to use a computer with mouse and keyboard and keep the camera on at all times.

Participation scores were calculated each week by multiplying the attendance and attentiveness scores. For instance, if a student was 10 minutes late in a 50-minute class, attendance was 80%. Likewise, if a student had the shared instructor desktop in focus only half of the time, the attentiveness score was 50%. If a student was 10 minutes late and did not keep the shared desktop in focus half the time, the participation score was 40%. At the end of the week, each day's participation score was posted to the gradebook for the class. For days when students were disconnected one or more times, the sum of the products for the partial sessions was used. At the end of the semester, students with average participation below 80% lost one letter grade, and two letter grades if below 60%.

The four classes in the study involved two face to face classes in computer labs and two Virtual Class Meetings. The university defines Virtual Class Meetings as follows: "Virtual class meeting courses allow students to use their home or university computer to attend class at designated times" (Northeastern State University, 2019). In other words, both formats are synchronous but virtual class meetings are location-independent and face to face classes are not. The same videoconferencing software was used in all classes. Face to face classes were taught in computer labs, did not use overhead projectors or whiteboards, and streamed the session directly to the students' lab computers. All applications were shared on the instructor's desktop. Various features of the videoconferencing software were used to increase student participation. Students could use annotation and drawing tools on the shared desktop to ask questions, post comments, and make annotations anonymously. The Chat feature was used to post questions and comments, and answers to instructor questions. Finally, having students take over control over mouse and keyboard was used to have students demonstrate their understanding on the common desktop. Regardless of online or local delivery, all these techniques were used to lesser or greater extent. Students in the face-to-face classes were also allowed to participate remotely to maximize attendance. No records were kept regarding local or remote attendance for face-to-face classes.

The first class, CS 3403 Data Structures, is one of the core classes in the curriculum. It was taught as a virtual class meeting twice a week for 75 minutes. The course covered common data structures and algorithms in Computer Science and used Python programming projects to illuminate the concepts. The final exam consisted of a comprehensive multiple-choice test worth 40% of the course grade. Twenty-nine students started the course, and 24 took the final exam.

The second class, CS 3643 Programming for Cyber Security, was an elective class taught as a face-to-face class twice weekly for 75 minutes. The course covered general cybersecurity concepts and problems and used virtual machines with Python programs to illustrate the material. The final exam consisted of a comprehensive multiple-choice test worth 40% of the course grade. Fifteen students started the course, and 11 took the final exam.

The third class, CS 4203 Software Engineering, is another core class in the CS curriculum. It was taught as a virtual class meeting thrice weekly for 50 minutes. The course covered the development process including analysis, modeling, and testing. UML models were developed with online software, and testing was done with a scripting language. The final exam consisted of a comprehensive multiple-choice test worth 40% of the course grade. Twenty-nine students started the course, and 28 took the final exam.

The final class, CS 4223 Game Programming, was an elective class taught face to face. The class met twice weekly for 75 minutes. The course was heavily project based with hands-on projects due every two weeks and used Unity with Visual Studio to develop the games. The final exam was an in-class programming project worth 30% of the course grade. Twenty-seven students started the course, and 22 students took the final exam. One student got a zero score for the final exam for failure to follow final exam instructions.

Activity Reports

The videoconferencing software can generate multiple reports. For this study, we used the details report which can list each login for each course meeting for a period of up to a month. Data include topic, join time, leave time, and the "attentiveness score." Attentiveness in this context was defined as the percent of time that the shared Zoom window was in focus. If a student was logged in but used another application, this did not contribute to attentiveness. If students got disconnected during class and connected again, each partial session would have its own attentiveness score. Unfortunately, the attentiveness score was removed from all reports during the COVID-19 crisis (Yuan, 2020).

4. SAMPLE STATISTICS

As usual in Computer Science, the majority of students were male, traditional full-time students in their late teens and early twenties who finished the course and took the final. Details are listed in Table 1.

course	female	male
CS3403	**7**	**22**
non-traditional	**1**	
final	1	
traditional	**6**	**22**
final	6	17
no_final		5
CS3643	**1**	**14**
traditional	**1**	**14**
final	1	9
no_final		5
CS4203	**7**	**22**
non-traditional	**1**	
final	1	
traditional	**6**	**22**
final	6	21
no_final		1
CS4223	**5**	**22**
non-traditional	**1**	
no_final	1	
traditional	**4**	**22**
final	3	18
no_final	1	4

Table 1 - Sample Statistics

Class attendance and attentiveness data were automatically recorded by Zoom, since students were required to log in to the class sessions. Participation scores were posted on the Blackboard gradebook every two weeks, and students who scored low on participation early in the course received an email with separate data for attendance and attentiveness to explain why their scores were low. Since we measured the influence of conditions in for each student in one course only, we used the final exam in the course to measure performance. The final multiple-choice exam was posted using the course delivery system and scores automatically calculated. Questions and answers were reviewed based on less than 50% correct answers, and no questions were found to be incorrectly stated.

5. ANALYSIS

The data was analyzed in anonymous form. Daily Activity Reports were downloaded in CSV files and copied to one sheet of a spreadsheet, final exam scores were downloaded from the Blackboard gradebook and copied to another sheet, and a third sheet was used as a lookup table with student names and random numbers between 1111 and 9999.

Next, we corrected for absences which were not reflected in the activity reports. All absences received a zero score for participation, as no time was spent in class. Absences were not corrected for excused absences, such as attendance of events sanctioned by Academic Affairs. Students who did not finish the class and did not take the final exam were included with a zero score for the final. Final exam scores were standardized to a percent of possible points by dividing the actual score by the maximum of 300 or 400 points.

Student names in the activity reports and the final exam scores sheet were replaced with the random numbers, and linked in a fourth sheet combining the student participation with their grades on the final exam. This sheet with random numbers, participation score, and standardized final exam score was exported in CSV format and imported in SPSS.

The data were analyzed with linear regression at the course level and at the semester level (all courses combined). Descriptive statistics show that some students reached perfect participation and perfect scores on the final exams. Appendix A lists the descriptive statistics first at the semester level, and then at the course level.

Linear regression at the semester level, with all courses combined, showed a statistically significant relationship between the independent participation variable and the dependent performance variable. The level of significance was .000 for the regression and .000 for participation. The R Square statistic was strong at .648, indicating that 64% of the variance in student performance was explained by student participation. Since we used only one independent variable, the unstandardized coefficient for participation was reviewed. At a level of 1.094, each percent increase in participation was related to about a percent of increase in performance. Appendix B shows the output of the semester level analysis.

At the course level, linear regression showed a similar result. The significance for regression in each course was .000, indicating a statistically significant relationship. The R Square statistic varied between a low of .465 and a high of .933. Coefficients for participation were all slightly above 1, again indicating that each percent increase in participation was related to about a percent increases in performance. Appendix C shows the output of the course level analysis.

6. CONCLUSIONS AND RECOMMENDATIONS

Based on these results, it appears that class participation, defined as the combination of coming to class and paying attention while there, is a good predictor of student performance. This would appear to be a no-brainer, but in this age where students often work significant hours and/or have family obligations, the importance of coming to class and spending this time productively should not be underestimated. Using the participation statistic as part of the total number of points in the course can also help motivate students to change behavior in a positive manner. When students notice that the participation score is low, it is easy to see whether this is due to being distracted in class, or not coming to class altogether. Since the videoconferencing software does not record attentiveness when students are not in class, the percent time in class is a perfect indicator for attendance and the attentiveness score a good indicator for focus while they are there.

This does not mean that attentiveness as measured by computer focus on the shared desktop is perfect. Students can keep other applications open, especially on dual monitors, and quickly click back and forth. The videoconferencing software only samples focus every 30 seconds. They can also use cell phones to play, and dependent on the positioning of the phone, this may not be very apparent even when the camera is on and students have to keep their face in view. Conversely, students could log with their cell phone and play on the computer if use of cell phones is not prohibited. Students could use two computers. It is even possible to record short videos with a webcam, leaving the meeting, and running the video as a background in a loop (Clark, 2020). Fortunately, there are many communication tools instructors can use to facilitate active participation. Chat boxes record messages by name, annotation pointers have names, students can have designated areas on the shared desktop to respond, individual students can be called on to take over control of mouse and keyboard, and so on.

Unfortunately, attentiveness tracking is no longer available in the videoconferencing software used. During the CoVid-19 pandemic, use of the software increased dramatically. This made it an attractive target for outsiders to intrude and disrupt the session with unwanted graphic content. In response, the software provider introduced several security and privacy measures, which unfortunately included the removal of the attentiveness score we used. Maybe it will be available in the future, and maybe in selected versions or subscription levels. In the meantime, this analysis demonstrates the benefit of not only attending class but paying attention while there. Future avenues for research include analyzing the data with attendance and attentiveness as separate independent variables. Due to the loss of attentiveness tracking, we also need to develop alternative measures of measuring active participation while in class and encouraging students to decrease lurking behaviors.

In the current educational climate with infectious diseases affecting course delivery mechanisms, we expect an accelerated move towards more flexible class formats. Courses do not have to be purely face to face, and students should be able to seamlessly switch between face to face and virtual formats. Allowing students to switch between face to face and synchronous virtual attendance will help to keep attendance high, and measures to increase two-way communication between instructors and students will help to maintain the quality of instruction.

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APPENDIX A: DESCRIPTIVE STATISTICS

Descriptive Statistics

	N	Minimum	Maximum	Mean
participation	100	0.5%	100.0%	77.075%
standardized as % of max score possible	100	0.0%	100.0%	67.790%
Valid N (listwise)	100			

Descriptive Statistics

course		N	Minimum	Maximum	Mean
2019Fall-CS3403	participation	29	7.0%	100.0%	74.162%
	standardized as % of max score possible	29	0.0%	96.0%	65.655%
	Valid N (listwise)	29			
2019Fall-CS3643	participation	15	0.5%	90.3%	60.993%
	standardized as % of max score possible	15	0.0%	90.0%	56.500%
	Valid N (listwise)	15			
2019Fall-CS4203	participation	29	45.6%	98.9%	86.510%
	standardized as % of max score possible	29	0.0%	100.0%	81.638%
	Valid N (listwise)	29			
2019Fall-CS4223	participation	27	6.4%	98.3%	79.004%
	standardized as % of max score possible	27	0.0%	100.0%	61.481%
	Valid N (listwise)	27			

APPENDIX B: COMBINED COURSES

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	participation[b]	.	Enter

a. Dependent Variable: standardized as % of max score possible

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.805[a]	.648	.644	18.7685%

a. Predictors: (Constant), participation

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	63501.016	1	63501.016	180.270	.000[b]
	Residual	34521.074	98	352.256		
	Total	98022.090	99			

a. Dependent Variable: standardized as % of max score possible

b. Predictors: (Constant), participation

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-16.496	6.552		-2.518	.013	-29.498	-3.493
	participation	1.094	.081	.805	13.426	.000	.932	1.255

a. Dependent Variable: standardized as % of max score possible

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APPENDIX C: SEPARATE COURSES

Variables Entered/Removed[a]

course	Model	Variables Entered	Variables Removed	Method
2019Fall-CS3403	1	participation[b]	.	Enter
2019Fall-CS3643	1	participation[b]	.	Enter
2019Fall-CS4203	1	participation[b]	.	Enter
2019Fall-CS4223	1	participation[b]	.	Enter

a. Dependent Variable: standardized as % of max score possible

b. All requested variables entered.

Model Summary

course	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
2019Fall-CS3403	1	.845[a]	.714	.703	17.6498%
2019Fall-CS3643	1	.966[a]	.933	.928	9.7440%
2019Fall-CS4203	1	.731[a]	.535	.518	12.4119%
2019Fall-CS4223	1	.682[a]	.465	.443	26.4172%

a. Predictors: (Constant), participation

ANOVA[a]

course	Model		Sum of Squares	df	Mean Square	F	Sig.
2019Fall-CS3403	1	Regression	20989.648	1	20989.648	67.379	.000[b]
		Residual	8410.903	27	311.515		
		Total	29400.552	28			
2019Fall-CS3643	1	Regression	17175.696	1	17175.696	180.899	.000[b]
		Residual	1234.304	13	94.946		
		Total	18410.000	14			
2019Fall-CS4203	1	Regression	4781.484	1	4781.484	31.038	.000[b]
		Residual	4159.464	27	154.054		
		Total	8940.948	28			
2019Fall-CS4223	1	Regression	15144.015	1	15144.015	21.700	.000[b]
		Residual	17446.726	25	697.869		
		Total	32590.741	26			

a. Dependent Variable: standardized as % of max score possible
b. Predictors: (Constant), participation

Coefficients[a]

			Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for	
course	Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
2019Fall-CS3403	1	(Constant)	-19.653	10.897		-1.803	.082	-42.012	2.706
		participation	1.150	.140	.845	8.208	.000	.863	1.438
2019Fall-CS3643	1	(Constant)	-5.520	5.253		-1.051	.312	-16.868	5.828
		participation	1.017	.076	.966	13.450	.000	.854	1.180
2019Fall-CS4203	1	(Constant)	-34.376	20.951		-1.641	.112	-77.364	8.613
		participation	1.341	.241	.731	5.571	.000	.847	1.835
2019Fall-CS4223	1	(Constant)	-30.553	20.400		-1.498	.147	-72.568	11.463
		participation	1.165	.250	.682	4.658	.000	.650	1.680

a. Dependent Variable: standardized as % of max score possible