Technology Mediated Education: A Boon or Bane for Learning Outcomes of Students

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Abstract

Use of digital technologies in institutions of higher learning is pervasive. These technologies provide students choices over what and how they learn. On the other hand, educators as well as policy makers are ambivalent about impact of these technologies on the student learning outcomes in particular and society in general. Surprisingly, there is scant research about the impact of these technologies and on appropriate blending of online and traditional face-to-face instruction. Using a large student-level dataset from a medium-sized university, we measure the impact of fully online, partially online and hybrid courses on learning outcomes. To resolve the issue of self–selection bias in estimating the of impact of different modes of instruction on learning outcomes, we utilize student and course characteristics as covariates and check the robustness of our results through multinomial propensity score matching. Surprisingly, we find that while the hybrid mode (online content between 20% and 50%) of instruction has a significant positive impact on student learning, fully online and partially online courses have a significant negative impact.

Keywords

Online educational technologies, mode of instruction, student learning performance, propensity score matching

Introduction

Over the last decade, United State's (US) universities are experiencing a steady rise in online course offerings and students enrollment in online classes (Allen and Seaman 2015). Growth in enrollment for online courses is being driven by students who are seeking flexible formats for courses, certificates, and degree programs to support career placement, advancement, and transition (Ginn and Hammond 2012). Students are also enrolling in online courses to pursue advanced studies while still engaged with full-time jobs. Interestingly, an increasing number of students enrolled in on-campus programs are also registering for hybrid to fully online courses throughout their period of enrollment at the universities (Allen and Seaman 2017).

In 2016, 56.1 percent of students who took only online courses resided in the same state as their institution – a number that has risen steadily from 50.3 percent in 2012 (Friedman 2018). Although overall enrollments in the US continued to decline over the past few years, online enrollments in higher education have continued to grow (Allen and Seaman 2017). According to WCET's (WICHE Cooperative for Educational Technologies) distance education enrollment 2016 report, from 2002 to 2014 the number of students enrolling in "at least one distance education course" increased from 1.6 to 5.8 million (Poulin and Straut 2016). Federal data suggested that in fall 2016 more than 6.3 million students in the US – most of whom were undergraduates – took at least one online course, which is significantly higher from the previous year (Friedman 2018).

To meet the growing demand of online courses, universities are also leaning toward online courses. Adoption of digital technologies by universities is also partly due to the vast improvement of instructional technologies and their ubiquitous presence as well as the intention to provide access and convenience to students at a lower cost (King and South 2016). Technology increasingly is being used to provide students more choices over what and how they learn and at what pace. It often helps them to organize and direct their own learning for the rest of their lives. Through various web-based learning platforms, virtual learning labs, educational games and simulations and augmented reality (AR), new technologies are making a lot of promises and often claim to have transformed learning.

Despite various promises and claims, the impact of these technologies on student learning outcomes is one of the most spirited topics of debate in the domain of educational technology, and education policy (Sitzmann et al. 2006). While organizations like the Bill and Melinda Gates Foundation and the Lumina Foundation strongly advocate for online education, academicians are more skeptical about the utility and efficacy of online learning (Krieg and Henson 2016; Zhang et al. 2004). This can be inferred from the fact that distance education enrollments remain highly concentrated in a relatively small number of institutions (Allen and Seaman 2017).

There is abundant literature which investigated the role of technology in education. Researchers have investigated the role of technology in facilitating the cognitive presence (Garrison and Cleveland-Innes 2005) and promoting equality of education opportunity (Jacob et al. 2016), and even the role of habit behind continuous usage of educational technology systems (Limayem and Cheung 2008). Though online education is a hot topic for ongoing debate in popular press, there is a scarcity of convincing evidence in the academic literature regarding the superiority of online education (Means et al. 2009). There are supports for all three different possible results. While some research reported significantly better performance of students who attended traditional, face-to-face sections of a course than those attended the same course online, others have found the opposite (Means et al. 2009). Yet another set of researchers found no significant difference in student performance between online and face-to face sections of the same course (Jahng et al. 2007). Apart from that, except a handful (Jaggars and Xu 2013; Jaggars and Xu 2011; Johnson and Mejia 2014), most of the studies addressing this issue did not report taking any precaution for self-selection bias which is quite commonplace for a naturally occurring dataset. Many of them did not have any control for variables, which can therefore possibly give rise to a confounding effect.

Lack of control for such confounding variables can easily distort the results in different possible directions. Therefore, the effectiveness of the findings of such studies in identifying effects of different modes of instructions on student's learning performance is quite limited. Finally, except a few (Jaggars and Xu 2013; Johnson and Mejia 2014; Xu and Jaggars 2014), most of these studies did not provide enough evidence in support of the robustness of their findings. Therefore, more systematic studies, which will carefully handle aforementioned issues and present more robust evidence in support of its findings are of high importance to the academicians and educational policy makers.

Numerous studies have compared student performance between face-to-face and online courses but did not clearly define their criteria of considering a course as online and often put hybrid or blended courses in the online bucket (Stack 2015). Apart from that, the definition of fully online course also varies in different studies. For example, while Jaggar and Xu (2011) have considered the online courses as one in which 51% or more of the instruction and student-teacher interaction is online, Johnson and Mejia (2014) considered courses in which at least 80 percent of the instruction is internet based as online. In the same study, Johnson and Mejia (2014) consider courses in which a substantial share of instruction (30 to 80%) is offered online as blended. The amount of interaction along with content delivered through the internet can have a significant effect on the student's learning outcome. Therefore, beside the face-to-face and fully online comparison, it is also quite important to compare students' performance between face-to-face, hybrid and partially online sections of courses. In our study, we looked at this research gap and developed a more fine grain understanding of the issue by comparing traditional face-to-face courses with different types of online courses (fully online, hybrid and partially online). In this regard, we address the following research question:

What are the effects of different online modes of instruction on the student's learning performance?

To address our research question we compare student's learning performance (course grade) for a larger and representative set of fully online, partially online and hybrid courses against a similar set of traditional, face-to-face courses. It is important to mention here that we have considered a course as fully online course if 100% of the instructions and student-instructor interactions are online. Courses that have less than 50% of the course content delivery and student-instructor interaction happening online are considered as hybrid courses. Partially online courses have more than 50% but less than 80% of the course content delivery and student-instructor interaction happening online. To assess the effects of fully online, partially online and hybrid courses on the student's course grade, we have developed four different regression models. To address potential self-selection bias, we gradually incorporated a set of student's demographic-related attributes, academic preparedness related attributes and course-related attributes to these models and finally checked for the robustness of our results by deploying the multinomial propensity score matching method. Our analysis yielded robust negative estimates for fully online and partially online modes of instruction in terms of course grade. For the hybrid mode of instruction we found a robust positive effect on the course grade.

Our study offers significant implications for the academicians, researchers and educational policy makers. The study suggests that both fully online and partially online modes of instruction have significant negative impact on the student's learning performance in comparison to traditional face-to-face learning. Surprisingly, for the hybrid mode of instruction our study have found a robust positive effect on student's learning performance in comparison to face-to-face mode of instruction. This finding also suggests that courses (hybrid) in which amount of online content delivery and student-instructor interaction remains under a threshold (<50%), can have a significant positive effect on students learning outcome in comparison to face-to-face courses. As the amount of online content delivery and student-instructor interaction goes beyond a certain threshold level, it can have a detrimental effect on student's learning performance.

Literature Review

Extant literature which has studied the effect of different modes of instruction on the learning outcome and course completion reported quite mixed results. While a set of studies has suggested superior learning performance for the online instruction mode, another set suggested inferior learning performance for the same. Yet another set found no significant difference between the learning performances for both online and traditional face-to-face instruction. Though such results are surprising, they are not completely implausible. All these different studies have defined online and face-to-face modes of instruction differently (Jaggars and Bailey 2010). They have deployed different methods to obtain their results (Jaggars and Bailey 2010; Kwak et al. 2015). Apart from that, these studies often target different student population and also have considered learning performance and course completion for a variety of subjects with different levels of advancement. While some of these studies (Krieg and Henson 2016) focused on long term or cumulative learning outcome, most of the studies were interested in immediate learning outcomes like course grade and course completion (Johnson and Mejia 2014). Finally, these studies were conducted with very different research objectives. In the following sections we will discuss these issues in detail.

In the contemporary literature related to online vs face-to-face learning, there exists a dearth of study which systematically compares online vs face-to-face learning outcomes by conducting a randomized experiment. Among the handful of such studies, Figlio et al. (2013) have conducted an experiment by randomly assigning students to live or online sections of an introductory microeconomics class. While Bowen et al. (2014) randomly assigned students between hybrid and traditional formats of instructions for a statistics course, Joyce et al. (Joyce et al. 2014) have conducted a randomized experiment with 725 students to compare student's course grade point between hybrid and face-to-face mode. Surprisingly, for Joyce et al. (2014) the fundamental difference between the hybrid and face-to-face is the amount of time spent in the classroom (the hybrid section only has half of the amount of formal class time as those in face-to-face format).

While Figlio et al. (2013) found modest evidence that live only instruction leads to better test scores in comparison to internet-based instruction, Bowen et al. (2014) found no significant difference in the learning outcome and concluded that hybrid mode does not harm to pass rates and final exam scores. Joyce et al. (2014) found that students in the traditional format scored 2.3 percentage points more than student's who took the course online on a 100 point scale on the combined midterm and final overall grade. While both Figlio et al. (2013) and Joyce et al. (2014) have considered students earlier academic performances (GPA, SAT score, ACT score, high school GPA) and ethnicity as control variables, Bowen et al. (2014) made effort to control for course level, student level and instructor level characteristics. While all three studies have done a commendable job, we are still not sure about the generalizability of their results across different subjects as each of these three studies have only considered a single subject.

To assess the effects of different modes of instruction on learning performance, most of the contemporary studies have used large existing datasets which are available to different universities, community colleges or federal institutions (Jaggars and Bailey 2010). Though there are several of such studies which compared students learning performance between online and face-to-face modes of instruction through an existing large dataset, most of them are descriptive in nature and took no precautionary measure for the student's self-selection issue (Means et al. 2009). There exists a small set of studies which has considered the issue of students' self-selection and deployed multiple robustness checks to show the robustness of their findings.

For example, a couple of studies conducted by Di Xu and her co-researchers deployed different statistical methods to address the issue of students' self-selection for courses and also to show the robustness of their findings. In one of their studies, Xu and Jaggars (2011) have used the multiple propensity score technique to find the effect of two different modes of instruction (Online and Face-to-face) on course attrition and successful course performance. In other studies, they have used different fixed effects (Xu and Jaggars 2014), instrumental variable (Jaggars and Xu 2013), multilevel regression technique (Jaggars and Xu 2011) and two stage least square (2SLS) technique to estimate the impact of online and face-to-face modes of instruction on course persistence and final course grade. While Xu and her co-researchers have considered different subjects for online and face-to-face modes of instruction, all of their studies have suggested robust negative estimates for online learning in terms of both course completion and final course grade. For instance, in one of their studies, Jaggars and Xu (2011) showed that for both introductory math and English courses students are more likely to fail or withdraw from the online course than face-to-face and hybrid courses. Students are equally likely to complete both the hybrid and face-to-face versions of the courses. Another study (Xu and Jaggars 2014) which has considered a substantial set of different subjects like social science, education, computer science, humanities, Math, etc. suggested that students perform more poorly in online courses than in face-to-face courses. Along with that, the study also found course persistence is significantly low for online courses.

Xu and Jagger (Jaggars and Xu 2013) also compared courses which have both online and face-to-face sections and have estimated the impact of modes of instruction on course persistence and final course grade. This particular study also found negative estimates for online learning. Though these studies have found robust negative estimates for the online mode of instruction in comparison to face-to-face, most of these studies have used datasets related to students of different state community colleges (Jaggars and Xu 2013; Jaggars and Xu 2011; Xu and Jaggars 2014). In spite of their robust estimation, it is still unclear whether these findings hold for general university students, as community colleges have a considerably higher rate of course attrition and withdrawal rate for their online courses (Jaggars and Xu 2013). Apart from that, a significant portion of community college students are low-income, working, have dependents and cannot have the time and money to retake the course that they did not complete successfully the first time (Adelman 2005; Bailey and Morest 2006; Planty et al. 2009). Therefore, along with state communality colleges, it is also important to compare the effect of fully online, partially online, hybrid and face-to-face modes of instruction on students' learning performance in public and nonprofit universities.

Though most of the studies have used course completion and final course grade as the outcome variable to estimate the effect of online mode of instruction on student's learning performance Krieg and Henson (2016) have used performance of a student in subsequent courses to find out the long-term effect of online modes of instruction. The study found that the student's grades in follow-up courses can be expected to be nearly one-twelfth of a grade lower if the prerequisite course was taken online. While considering the short-term outcome, Johnson and Mejja (2014) found that in short term student outcomes are worse in online courses than in traditional face-to-face courses. Interestingly, the study also found that students who took at least some online courses are more likely to earn an associate degree than those who took only traditional courses (Johnson and Mejia 2014).

Researches related to the effect of online learning are not always focused towards the objective outcomes like course completion and final course grade. In their study Yukselturk and Bulut (2007) tried to identify different factors that affect the student success in an online computer programming course. The study found that variables related to self-regulation (cognitive strategy use, self-regulation) have significant effect on student's success score. The study also concludes that successful students generally use self-regulated learning strategies in online course.

Though all the above-mentioned studies have compared student's learning performances for online and face-to-face courses, none of them have studied the effect of fully online, partially online and hybrid modes of instruction on student's learning outcomes. Therefore, based on the above literature review and informed by other important literature in this domain we hypothesize that

H1) The fully online mode of instruction has a significant negative impact on the student's learning outcome measured through course grade.

H2) The partially online mode of instruction has a significant negative impact on the student's learning outcome measured through course grade.

H3) The hybrid mode of instruction has a significant negative impact on the student's learning outcome measured through course grade.

Empirical Approach

To assess the effect of different blends of online mode of instructions (fully online, partially online and hybrid), we used regression techniques, beginning with an OLS models for course grade. We started with the simplest ordinary least squires (OLS) model:

$$Y = \alpha + \beta_1 \text{ PartiallyOnline} + \beta_2\text{FullyOnline} + \beta_3\text{Hybrid} + \mu \quad (1)$$

Where PartiallyOnline, FullyOnline and Hybrid are the key explanatory variables and each of them is equal to 1 if the mode of instruction for the course was partially online, fully online and hybrid respectively. We have considered Face-to-Face mode of instruction as the base level.

In our second model we have included a set of student's demographic attributes (age, gender, IPEDS race) as covariates to control for their effects on the course grade. X represents the vector which incorporates all the covariates related to student's demographic attributes mentioned above.

$$Y = \alpha + \beta_1 \text{ PartiallyOnline} + \beta_2\text{FullyOnline} + \beta_3\text{Hybrid} + \lambda X + \mu \quad (2)$$

Along with the key explanatory variables and a set of student's demographic covariates our third model incorporated a set covariates representative of student's academic preparedness (Enrollment Status, Class Level, Highest Degree Held by the Student, Transfer GPA, Total Units, Transfer Units, Total GPA, GPA Earned at the Current University, Age of Enrollment at the University, Number of Years since Graduating from High Schools, High School GPA, Degree Objective, Credit Option, SAT Writing Score, State University Fee Waiver Status, Enrollment status at the Educational Opportunity Program). Therefore our third model also accounts for a set of student's attributes which represent his/her academic preparedness and are known for affecting students learning outcomes. In model 3, Z represents the vector which incorporates all the covariates related to student's academic preparedness mentioned earlier.

$$Y = \alpha + \beta_1 \text{ PartiallyOnline} + \beta_2\text{FullyOnline} + \beta_3\text{Hybrid} + \lambda X + \delta Z + \mu \quad (3)$$

Finally to control for effects generated by different subjects offered during the semester our final model included 90 subject related dummy variables as covariates. Therefore our final model controls for student's demographic attributes, academic preparedness related attributes and different subjects (91) offered during the semester. In model 4, S represents the vector which incorporates all the covariates related to different courses offered during the semester.

$$Y = \alpha + \beta_1 \text{ PartiallyOnline} + \beta_2\text{FullyOnline} + \beta_3\text{Hybrid} + \lambda X + \delta Z + \gamma S + \mu \quad (4)$$

Data

Data for this project come from a regional, comprehensive university that annually enroll about 39,000 students in 134 different bachelors and masters granting programs corresponds to 70 different fields. In the most recent years, the university admitted 48% of the applicants. The average math and verbal SAT score of incoming freshmen are about 1050. The current graduation rate is about 47%. The university operates on a quarter system and typically offers many sections of the same course each quarter. Our primary analysis was performed on a data set containing 39950 degree seeking students who enrolled in the university during the fall term 2016. Their cumulative enrollment generated a total of 183,000 observations for 91 different subjects offered through a total 6072 sections.

In terms of demographics, the data set provided information on each student's gender, ethnicity, age and a variety of other characteristics. Unfortunately the data set provides no information about students socioeconomic quantile of the census area in which the student lives (SES) which is often considered other studies (Xu and Jaggars 2014) as one of the controls for student demographics. Regarding students' academic preparedness the dataset provides information related to student's enrollment status, class level, highest degree held by the student, transfer of GPA, total units covered by the student, number of units transferred for the student, Total GPA of the student, GPA earned by the student at the current university, student's age during the first enrollment, number of years since high school graduation, High School GPA, degree objective, choice of course credit, SAT writing score, state university fee waiver status, enrollment status at the educational opportunity program, etc. The data set also included information on each course, such as course number, course subject, mode of instruction, final grade earned in the course (ranging from a failing grade of 0.0 to an excellent grade of 4.0, including decimals such as 2.8). Apart from that the data set also provided us the information related to course persistence. This provides us the information if the student remained enrolled in the course until the end of the semester or withdrew his/her enrollment before the end of the semester. Our final sample included 136156 course enrollments by 21,988 students for 91 different subjects offered through a total 2608 sections.

Results

Across the 136,156 course enrollments in the final sample, 69.09% of the course enrollments were for face-to-face sections, 8.73% for fully online sections, 1.90% for partially online sections and 20.25% for hybrid course sections. Table 1 and Table 2 presents summary statistics of some of the important student's characteristics.

	Mode of Instruction			
Variable	Face-to-face Mean (Std.Dev)	Partially Online Mean (Std.Dev)	Fully Online Mean (Std.Dev)	Hybrid Mean (Std.Dev)
Age	23.70 (5.98)	23.62 (4.66)	23.53(5.51)	21.76(4.34)
Transfer Units	33.40(39.22)	43.82(39.71)	35.01(38.60)	27.52(35.86)
Transfer GPA	1.61(1.58)	2.075(1.485)	1.791(1.568)	1.48(1.58)
GPA Earned at the Current University	2.20(1.43)	2.40(1.12)	2.45(1.18)	2.12(1.33)
Total Units	66.95(43.01)	86.07(32.29)	74.13(33.06)	58.43(36.72)
Total GPA	2.59(1.18)	2.84(0.58)	2.870(0.69)	2.52(1.09)
Age of Enrollment at the University	21.96(5.80)	21.42(4.74)	21.49(5.48)	20.26(4.21)
Number of Years since Graduating from High School	4.51(4.62)	4.91(3.68)	4.78(4.60)	3.21(3.63)
SAT Writing Score	229.52(237.66)	221.12(234.46)	250.62(237.53)	295.23(230.78)

Table 1. Summary statistics of students' academic preparedness related attributes

Variable	Categories	Face-to-face	Partially Online	Fully Online	Hybrid
Gender	Male	53.32%	57.12%	66.84%	53.05%
	Female	46.68%	42.88%	33.16%	46.95%
IPEDS race	No Information Available	0.14%	0.003%	0.001%	0.058%
	White only - Non Hispanic	25.41%	27.65%	25.378%	23.291%
	Black or African American only - Non Hispanic	5.09%	4.97%	5.294%	4.063%
	American Indian or Alaskan Native only - Non Hispanic	0.16%	0%	0.218%	0.123%
	Asian Only - Non Hispanic	14.26%	18.55%	12.168%	13.971%
	Native Hawaiian or Other Pacific Islander only - Non Hispanic	0.08%	0.19%	0.168%	0.130%
	Two or more races - Non Hispanic	3.80%	3.355%	3.697%	3.820%
	Hispanic/Latino (any race)	45.58%	40.879%	47.554%	49.842%
	Unknown Race	5.46%	4.357%	5.378%	4.698%
Enrollment Status	Continuing student	70.560%	81.565%	81.521%	72.717%
	Returning student	0.450%	0.038%	0.411%	0.261%
	Returning transfer	1.129%	2.930%	1.983%	1.094%
	New transfer	10.261%	13.305%	12.806%	10.346%

	First-time student Transitory student	17.198% 0.398%	1.966% 0.192%	2.369% 0.907%	15.425% 0.155%
Class Level	Freshman Sophomore Junior Senior Postbac	17.20% 9.33% 24.72% 36.17% 12.57%	6.40% 10.99% 31.50% 50.94% 0.15%	8.38% 18.37% 32.79% 35.71% 4.73%	27.07% 19.76% 27.61% 23.97% 1.57%

Table 2. Summary statistics of important student characteristics

While course withdrawal was 0.36% for the face-to-face courses, for fully online, partially online and hybrid courses they were 0.2%, 0.42% and 0.31% respectively. Interestingly, we did not observe any significant difference in the course persistence for all four different modes of instructions. For all four modes of instructions course withdrawal was below 0.5% of the course enrollment. In this regard our result did not corroborate with the findings reported by Xu and Jaggars (2014), Jaggars and Xu (2013), Jaggers and Xu (2011) who found a course persistence to be significantly low for online course.

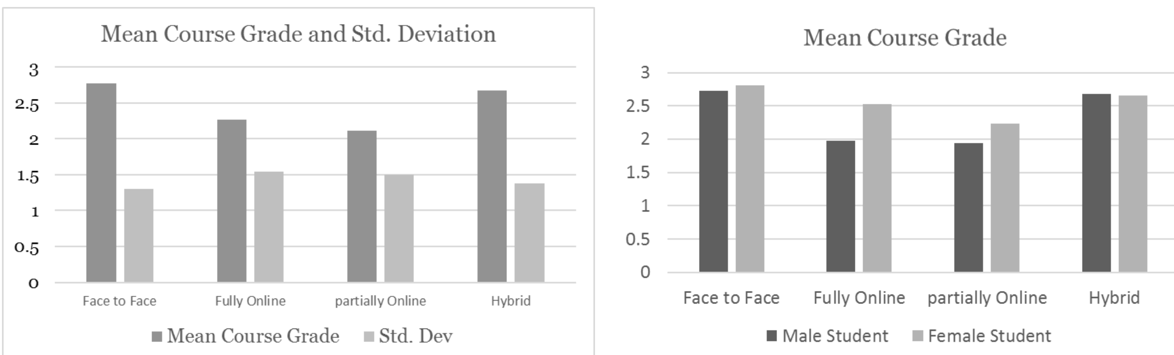

Figure 1 (a) Mean course grade std. deviation for all four modes of instructions and (b) Mean course grade for male and female students across all four mode of instructions

While we did not observe any significant differences in course persistence for different modes of instructions, we found that considerable gaps exist in mean course grades between face-to-face, fully online and partially online courses. On an average a student typically received lower grades in fully online (2.27) and partially online (2.112) courses in comparison to face-to-face (2.77) sections of the same courses. Though we did not find any significant difference between the face-to-face and hybrid (2.67) sections of the same courses. Figure 1 (a) shows the differences in mean course grades and standard deviations for all four modes of instructions. Surprisingly except for the hybrid, we observed considerable differences in mean course grades between male and female students for all three other modes of instruction. Female students, on an average, performed better than their male counterparts and this performance gap were more pronounced for the fully online and partially online mode of instruction. Figure 1 (b) shows the differences in mean course grades between male and female students for all different modes of instructions.

Descriptive statistics of our study also suggests significant performance gaps between students belonging to different races for all four modes of instructions. Table 3 shows the details of student performance for all four modes of instructions across different races.

IPEDS Race	Mean Course Grade for all Type of Course	Mean Course Grade for Face-to-face	Mean Course Grade for Partially Online	Mean Course Grade for Fully Online	Mean Course Grade for Hybrid
White	2.85	2.98	2.21	2.42	2.91
Black or African American	2.35	2.43	1.97	2.13	2.27
American Indian or Alaskan Native	2.46	2.66	-	1.72	2.24
Asian	2.71	2.85	2.22	2.21	2.90
Native Hawaiian or Other Pacific Islander	2.75	3.12	0.4	2.24	2.92
Two or more races	2.72	2.82	1.94	2.42	2.71

Hispanic or Latino	2.54	2.66	2.00	2.22	2.50
Unknown Race	2.76	2.86	2.33	2.36	2.91

Table 3. Mean course grade of students with different IPEDS race

Though the performance gaps were narrow for face-to-face and hybrid courses, they were quite pronounced for face-to-face, fully online and partially online courses. While examining the performance gaps across different races we found that the gaps between face-to-face, fully online and partially online courses were most pronounced for African Americans, Native Hawaiians, and Hispanics. In this regard our findings are quite similar with the observations made by Johnson and Mejia (2014), who also suggest bigger size of the gap for Latino and African-American students. Estimates of β_1, β_2 and β_3 along with their standard errors for all four different OLS models are presented in the Table 4.

Mode of Instruction Base: Face-to-face	Model 1 (without any Control) Coefficient (Standard Error)	Model 2 (Covariates: demographic characteristics) Coefficient (Standard Error)	Model 3 (Covariates: demographic characteristics, academic characteristics) Coefficient (Standard Error)	Model 4 (Covariates: demographic characteristics, academic characteristics, Subject and course characteristics) Coefficient (Standard Error)
Partially Online	-.664*** (0.272)	-.701*** (0.026)	-.121*** (0.019)	.010 (0.022)
Fully Online	-.101*** (0.013)	-.125*** (0.013)	-.044*** (.009)	-.087*** (0.010)
Hybrid	-.498*** (0.009)	-.415*** (0.009)	.094*** (0.007)	.116*** (0.008)
Significance code: ***=.001, ** =.01, *=.05				

Table 4. Estimated coefficients for different mode of instructions and standard errors for all four different empirical models

Our first empirical model (Model 1) suggest that the fully online (-.101), partially online (-.664) and hybrid (-.498) mode of instruction all have significant negative relationship with the students course grade. These significant negative relationships remain consistent even if we include a set of student's demographic related covariates to the model (Model2). Interestingly, as we further inserted, a set of students' academic preparedness related covariates to the model (Model 3) along with student's demographic related covariates the direction of the relationship between the hybrid mode of instruction and course grade changes to positive though the relationship still remained statistically significant at 0.001 level. The direction and level of significance remain unchanged for fully online and partially online mode of instruction. Finally, we incorporated covariates related to different subject and course characteristics to Model 3 to create our final model (Model 4). We found that the relationship between partially online mode of instruction and course grade changes its direction and also become statistically insignificant, though there were no changes in the direction and significance level for the fully online and hybrid mode of instruction. The inconsistency of the direction of estimated coefficients showcases the possibility of an inherent difference between groups of students' pursuing courses with different modes of instruction. This also suggests that the students may have self-selected themselves for different modes of instructions based on their inherent strength and weaknesses. To address the possible presence self-selection bias we have conducted robustness check with help of propensity score matching method.

Robustness Check

For the final model specification we used a range of propensity scores that are fairly balanced) (see table 5 -Region of common support). We have used all the covariates those were there in the Model 4 to calculate the propensity scores. For propensity score matching we have used stratification method which divides the range of variation of the propensity score in intervals in a manner that within each interval treated and control units have on average the same propensity score. Stratification method uses individual block to calculate propensity scores. For practical purposes the same blocks identified by the algorithm that estimates the propensity score can be used. Since we were interested in using all our covariates block by block and didn't want to go across blocks, stratification method became our primary choice. Within each interval (block) in which both treated and control units are present, the difference between the average course grade of the treated (fully online, partially online and hybrid) and the control (face-to-face) is

Stratification Method	Partially Online	Fully Online	Hybrid
Average effect of Treatment on the Treated (ATT)	-0.093	-0.028	0.060
Standard Error	0.012	0.012	0.006
t Statistic	-7.840	-2.086	9.564
Region of Common Support	[0.0003, 0.2167]	[0.0017, 0.3886]	[0.0060, 0.8409]
Number of Blocks	15	12	31
Number of Observation Considered (Treatment)	2383	10875	26191
Number of Observation Considered (Control)	81250	81486	81591
Method for Estimation of Propensity Score	Multinomial Logit Regression	Multinomial Logit Regression	Multinomial Logit Regression

Table 5. Multinomial propensity matching statistics

computed. Finally average effect of treatment on the treated (ATT) was obtained as an average of ATT of each block with weights given by the distribution of treated units across blocks. Table 5 shows all the important details regarding our robustness check by using the method propensity score matching. Our final findings indicate significant negative impacts of fully online (ATT: -0.028) and partially online (ATT: -0.093) mode of instruction on course grade which supported our hypothesis 1(H1) and hypothesis 2 (H2). We also found a significant positive impact of the hybrid mode of instruction (ATT: 0.060) on course grade. Therefore, we did not find any support for our hypothesis (H3) which suggested a significant negative impact of the hybrid mode of instruction on students learning outcome.

Limitation and Future Work

Although we would have preferred to investigate the robustness of our finding over a period of time, due to the limitation of our current data set we were unable to do so. Limitation of our current dataset also limits our ability to investigate the impact of modes of instruction while varying the amount of online content delivery as well as student-instructor interaction. Apart from that due to the limitation of the current dataset we cannot control for the instructors' characteristics, characteristics of a particular institution within the university (schools or colleges) which might have an impact on the students learning outcome. Since the data set we are working on originates from a single university our results might not generalize for all. Future research should consider all these issues to generate generalizable estimation of the impact of different modes of instruction on students learning outcomes.

Conclusion

Researchers, practitioners and policymakers are concerned about the effectiveness and future prospects of using technology as the sole mode of instruction at the institutions of higher education. Different stakeholders are still ambivalent about the real value addition done by the technology as mode of instruction. Our study addresses this research gap. We used OLS regression and multinomial propensity score matching to investigate the impact of fully online, partially online and hybrid mode of instruction on students learning outcome on a data set from a comprehensive regional state university. Our results suggest that while fully online and partially online mode of instruction has significant negative impact on the students learning outcome, hybrid mode of instruction has significant positive impact on the students learning outcome. Though technology oftentimes projected as the silver bullet for all learning related issues faced by institutions of higher education, academicians and policy makers should remain vigilant about the real value that the current state of technology is offering to ensure that technology mediated education turns out to be a boon for students who are the key stakeholders of institutions of higher learning.

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