Impact of an Orientation on Online Students' Course Outcomes

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Abstract: Online course taking is widespread in K–12 education and even more so as schools have turned to virtual learning during the global health crisis. Educators across the country are actively seeking evidence-based guidance, only to discover that there is limited rigorous research related to online learning. The need to understand how to prepare students to learn in an online environment has become more urgent. Orientations are cited as a best practice; however, there is no causal evidence to support that recommendation. In a randomized controlled trial, we found no significant differences in online course outcomes between high school students who were assigned an orientation and those in the business-as-usual group, though the timing of enrollment acts as a moderator.

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Introduction to the Problem

Online course taking has become ubiquitous in both K–12 and postsecondary education across the United States (Gemin & Pape, 2017), even more so as schools transitioned to remote learning in response to the COVID-19 global pandemic. As of 2015, national estimates suggest that 59% of public high schools offered fully online courses, and over half a million public 12th-grade students alone took supplemental online courses (National Center for Education Statistics, n.d.; U.S. Department of Education, 2015).[i] Now, nearly all students have had some experience with virtual learning. At the same time, students in online courses continue to have low completion rates in comparison to in-person courses (e.g., Freidhoff, 2020; Heinrich et al., 2019; Stallings et al., 2016), though some studies have not found any differences or the opposite (e.g., Heppen et al., 2017; Hughes et al., 2015). Given the widespread use of online courses, the need to understand how to prepare and support students to learn in an online environment has become even more urgent.

Currently, orientations to online courses are cited as a best practice as a means to familiarize students with the online environment and increase secondary students' course completion rates (e.g., iNACOL, 2011; Virtual Learning Leadership Alliance and Quality Matters, 2019; Watson & Gemin, 2009). In fact, they are a requirement for many online programs to become accredited. Although common sense would indicate that orientations are an appropriate support to provide to online students, like many best practices in online learning, there is no causal evidence to support that recommendation. In partnership with the Michigan Department of Education (MDE) and Michigan Virtual (MV), we conducted a randomized controlled trial (RCT) in fall 2018 to estimate the impact of an online orientation on high school students' course outcomes. This study focused on students who take supplemental online courses for the first time—that is, when students in brick-and-mortar schools take one or more courses online. The impetus for this study centered on MV's interest in using evidence to inform decisions about how to onboard its online students, and the shared interest of MV and MDE in providing guidance to all schools in Michigan about how to best support online students in their classes.

Review of the Literature

Most K–12 schools across the nation permit students to complete some of their coursework online; 32 states allow statewide online schools, 21 states have state virtual schools (generally, supplemental online course programs that are state-supported) with over a million enrollments, and many more offer district-based digital learning (Digital Learning Collaborative, 2020). Online courses for secondary students offer an opportunity to prepare students for online courses in the postsecondary setting. Additional commonly cited benefits of online course-taking relate to the opportunities to offer individualized instruction and widened education access, especially with regard to remedial, language, or advanced courses as well as credit recovery, which may not be offered at a student's current school (Heinrich et al., 2019; Rickles et al., 2018; Authors, 2015). Districts also use online credit recovery programs to increase graduation rates (Digital Learning Collaborative, 2020; Dynarski, 2018).

As schools have sought options for students to continue their learning as a result of COVID-19, educators across the country are actively seeking evidence-based guidance, only to discover that there is limited rigorous research related to online learning, and how best to support students in their online courses. Our exploration of the Institute of Education Sciences' What Works Clearinghouse (WWC), which reviews the existing research against a set of standards, indicates there are only three studies focused on online courses that met WWC standards with or without reservations: One study focused on postsecondary (Bowen et al., 2013), one focused on access to algebra online (Heppen et al., 2012), and one compared online to face-to-face credit recovery courses (Heppen et al., 2017). Even in a recent summary of the evidence of the effectiveness of technology, five of the six studies that were used to draw conclusions about online versus face-to-face learning were at the postsecondary level (J-PAL Evidence Review, 2019).

Theoretical Argument for Orientations to Online Courses

Although rigorous research to guide online programs and schools about effective practices to support students is limited, the existing literature does suggest that students "not only need to learn a subject online but need to learn how to learn online" (Lowes & Lin, 2015, p. 18). This is because online course experiences often differ considerably from the typical face-to-face learning environment. For example, students may experience a mix of synchronous and asynchronous instruction, thereby requiring more time management and self-regulation (Taylor & Dunn, 2015). Additionally, students may have to be more assertive in seeking out instructor support. Because of larger student enrollment, course instructors often have limited personal interaction with students, and therefore they may not be able to as easily identify and support struggling and disengaged students (Brunet, 2011).

Students in online courses may not expect that the course will be as challenging as a face-to-face course, may struggle with time management or self-regulation, and may not be as familiar with the technology or modes of communication in an asynchronous learning environment—all of which are important for student success in these courses (Artino & Stephens, 2006; Bozarth et al., 2004; Carruth et al., 2010; de la Varre et al., 2010; de la Varre et al., 2014; Yukselturk & Bulut, 2007). Consequently, such factors have been linked to higher dropout rates for students enrolled in online courses compared to face-to-face (Freidhoff, 2020; Heinrich et al., 2019; Stallings et al., 2016).

Orientation tools for online learning have been credited as important for helping students, especially those new to online learning, understand the online environment before starting courses (Beyrer, 2010; Harrell, 2008; Jagannathan & Blair, 2013) and address the challenges that students face related to time management and self-regulation. Additionally, Roblyer and Davis (2008) noted that orientations “can make a significant contribution to success … [and those] that specifically address how to organize and work in online environments could be especially useful to at-risk students.” Orientations are also thought to increase students’ self-efficacy, which in turn can have a positive influence on motivation and student achievement (Abdous, 2019; Wäschle et al., 2014).

Practitioner Support for Orientations to Online Courses

Orientations are commonly offered and often cited as a best practice (Virtual Learning Leadership Alliance and Quality Matters, 2019; Watson & Gemin, 2009). For example, the iNACOL (2011) *National Standards for Quality Online Courses* includes the following as an element under the standard Instructor and Student Support: “Students are offered an orientation for taking an online course before starting the coursework” (p. 19). It recommends that the course cover the experience of learning online, what is needed to manage challenges successfully, time commitments, software and hardware requirements, and how to set up the computer and work environment. Adelstein and Barbour (2016) compared the elements under each of the iNACOL standards to contemporary K–12 and higher education online course literature and found support for orientations in two handbooks for online teacher practice

(Elbaum et al., 2002; Rice, 2012). More recent standards (i.e., *National Standards for Quality Online Programs*) indicate that online learning programs should provide students with “an orientation to online learning technologies and successful online learning practices” (Virtual Learning Leadership Alliance and Quality Matters, 2019).

Research Basis for Orientations to Online Courses

Further, although it’s limited, the research on the use of orientations with postsecondary students suggests that it may improve student outcomes. After the implementation of Online Student Success—a 6-week, self-paced mid-semester orientation—at a community college, 78% of students who had been successful in the orientation achieved a passing grade in their online courses compared to 38% of a previous cohort of students who did not take the orientation (Beyrer, 2010). Attending an optional 1-hour orientation prior to beginning a course was also associated with higher grades in online undergraduate courses (Wojciechowski & Palmer, 2005). Additionally, the completion of an optional five-module interactive orientation that presented content with multiple modes in text, images, and videos was also associated with self-reported online learning readiness in social, technical, and communication skills (Liu, 2019).

Other studies have resulted in more mixed findings. One study at a community college found no significant difference in retention between students who did and did not take a four-module orientation prior to the start of their course (Koehnke, 2013), although the author was comparing two cohorts that were 5 years apart. In another study, two of the five undergraduate courses that received a 10-minute interactive orientation video showed a reduction in the percentage of students who withdrew compared to the previous year, and three showed statistically significant increases in the percentage of students earning A–C grades (Taylor et al., 2015).

The material covered in the orientations administered across these studies was noticeably similar. In addition to teaching students how to effectively use the learning management system (e.g., completing and submitting assignments, posting to discussions, locating grades and instructor feedback), several of the orientations also addressed online course etiquette, tips on successful online learning, time management, and basic computer functions. The orientations differed based upon their length and completion requirements, with some more comprehensive and interactive than others.

An important limitation persistent among prior studies of online orientation courses is the lack of experimental or quasi-experimental research design. Each of the aforementioned studies compared the outcomes of students who voluntarily enrolled in an online orientation course versus those who received an offer to enroll but did not. Self-selection into the treatment sample may be correlated with unobserved factors, such as motivation, that may result in improved outcomes. As such, this study addresses an important gap in the research by using a rigorous experimental design and examining the impact of online orientation courses on student outcomes.

Research Questions

This article will address the following primary and secondary research questions focused on high school students who took an online course for the first time:

(1) How does enrollment in an online orientation impact students' online course outcomes?

(2) Does type of course, timing of enrollment, or grade level moderate the relationship between enrollment in an online orientation and students' online course outcomes?

(3) Are students who *complete* the orientation more likely to complete their online courses?

We also conduct a number of sensitivity analyses to confirm that our results are robust across specifications.

Methods

Context

Nearly 90,000 high school students took an online course in Michigan during the 2017/18 school year, 11,573 of whom enrolled in an online course with MV (Freidhoff, 2019). The proliferation of online course enrollments in Michigan is partially on account of the legislative requirement that students complete at least one online learning experience to graduate and that a student's district pays for the expenses associated with the online course (Michigan State Aid Act, amended 2015). With so many students across the state enrolled in online courses, MDE and MV were interested in identifying ways to support students in completing their online courses and improving their course performance.

Studies in Michigan mimic the studies described above, where students enrolled in online courses complete them at lower rates than their in-person courses (e.g., Freidhoff, 2019; Freidhoff, 2020). MV faced similar concerns, with 79% of student enrollments receiving a status of "Completed/Passed" in their online courses in 2017/18 compared to 91% of these students receiving the same status in their non-virtual courses (Freidhoff, 2019). Although MV's completion rate is higher than those reported by other online programs in the state (average of 57% across other programs; Freidhoff, 2019), it means that over 2,000 students taking an online course through MV either did not complete their course or failed it. Since students are taking online courses to fulfill the state's online learning requirement, to complete credits needed for graduation, or to recover credits for a course that they previously failed, not succeeding in their online course can potentially put them in jeopardy of not obtaining a high school diploma.

As described above, offering students an orientation is considered a best practice in online learning. In fact, during MV's accreditation process, its accreditation agency indicated that it was a requirement. Yet, there is no causal evidence to support this requirement. MV was particularly interested in understanding whether an orientation impacts students' online course outcomes to inform its own approach as well as to inform the larger online learning community, many of whom consider an orientation to be a necessity for online students. With students, families, and schools making decisions about online learning, evidence-based support for how to help students be successful in online learning is paramount. Thus, this study aims to understand this requirement and determine whether an online orientation improved student completion rates.

To meet this aim, we employed a student-level RCT design because the purpose was to estimate the impact of being assigned the orientation, called Strategies for Online Success (SOS), on students' online course outcomes. By randomly assigning students into SOS or business-as-usual (BAU) supports, the results can be interpreted as causal. BAU in this study included pre-existing introductory materials to online courses. Thus, the experimental contrast was specific to what SOS does over and above other pre-existing introductory materials.

Data

This study relied on secondary data from the online course provider, MV, and from MDE. The data from MV included data related to student enrollment in the online course, such as the subject area of the course and timing of enrollment. The data also contained corresponding course activity, such as weekly logins, points earned, points attempted, and course grade. Additionally, the data included an indicator for whether the student was enrolled in SOS (i.e., treatment status) and data related to completion of each component of SOS. MDE provided administrative and assessment data through the Michigan Center for Educational Performance and Information, which houses the state’s educational data. The administrative data included student background data, such as race, gender, grade, Individualized Education Program and limited English proficient status, an indicator for whether the student was economically disadvantaged, and school enrolled.

This study compared the course outcomes for students who were assigned SOS to students who received BAU supports. The outcome variable was operationalized as a categorical variable wherein the student (a) completed the course earning at least 60% of the course points (referred to as completing the course), (b) did not earn 60% of the course points or dropped the course after the grace period (referred to as not completing the course), or (c) dropped the course during the grace period. MV established that a course is complete if a student earns 60% or more of the total course points. This cut-off represents a passing grade in most high schools in the state. However, the final grade on a student’s transcript is determined by a staff member at the brick-and-mortar school.

The sample consisted of high school students taking an online course for the *first time*. As a result, a pre-intervention outcome measure at baseline was not available. Therefore, we relied on the eighth-grade state assessment scores and prior year attendance to assess the equivalence of the two randomly assigned groups (treatment, BAU). As the study sample was not limited to a specific grade in high school, the eighth-grade assessments scores were used rather than an assessment from the prior year, because the only statewide assessment in high school occurs during 11th grade. To complement the eighth-grade assessment score, we used the prior year attendance rate because attendance is among the best predictors of high school course performance (e.g., Allensworth et al., 2014).

Sample

In fall 2018, 8,256 students who enrolled in online courses through MV were randomized into treatment and BAU groups. Students were randomly assigned to the treatment and BAU groups daily during the enrollment period. An algorithm was used each day on the list of students who enrolled in an online course. The students who met the eligibility criteria were each randomly assigned a number, sorted by those numbers, and half were batch enrolled in the orientation in addition to their regular spring courses. Those in the BAU group were enrolled in their regular spring courses but were not enrolled in SOS.

There were three possible course start dates for students enrolled in MV courses in fall 2018: August 20, August 27, and September 4. Students could enroll in a course prior to the course start date and up until 3 weeks after the course start date, which was considered the end of the grace period for adding or dropping courses. The semester was approximately 21 weeks long and ended in February 2019. For students who were enrolled in more than one online course, only one of their courses was randomly selected for inclusion in the analyses. In the exploratory analysis, timing of enrollment was used as one of the predictors because of its possible association with student motivation for the course. Randomly selecting a course ensured that the analytic sample is not biased in terms of timing of enrollment or student motivation for the course.

Of the 8,256 students who enrolled in an online course during fall 2018 through MV, 2,516 were successfully merged with the administrative and assessment data from MDE. Data between the two systems were merged based on an algorithm that included names and dates of birth, among other information, because the two systems do not use a common student identifier. If either variable did not match or was missing, then the data could not be merged. The primary reason for not being able to merge the data was missing or incorrect birthdates. Because schools enroll students in online courses in batches, the school staff member enrolling students may provide an inaccurate birth date, which could be because they lacked the information or because it was onerous to provide that information for each student. Thus, we examined the representativeness of the study sample as an unbiased sample from the population of students enrolled in MV by comparing the online course characteristics of the matched and unmatched samples (Appendix, Table A1). Because of differences in online course characteristics between the matched sample and the unmatched sample, the results only generalize to those students who can be matched between the two data systems. We also performed a sensitivity analysis with all 8,256 students (discussed below) and found similar results.

After excluding students who had already had an online learning experience prior to fall 2018 and those not in high school, the final sample was narrowed to an analytic sample of 1,781 students. These students were in 352 sections across 126 courses; 910 students were in the treatment group (51%) and 871 students were in the BAU group (49%). Approximately 45% of the students were in Grade 12, 27% were economically disadvantaged, and 47% were female. Only 4% of the sample had an Individualized Education Program and less than 1% were classified as limited English proficient. The sample was 85% White, 3% African American, 4% Hispanic, and 4% Asian. Five percent reported a different race.

In terms of the types of courses, 70% of students were enrolled in a core course. Core courses are part of the core academic curriculum, including mathematics, English language arts (ELA), science, social studies, and world language. Non-core courses include other types of courses such as physical education or electives. World language was the most common subject areas, with 30% of students enrolled. Only 52% of students enrolled prior to the course's official start date (referred to as on-time), suggesting that many students enrolled on or after their online course started (Table 1).

[Insert Table 1 here]

Treatment Contrast

Students in the treatment group were enrolled in SOS, an asynchronous orientation developed by MV. SOS prepares students for the transition from taking courses in person to taking them online. As MV and MDE were interested in supporting students across the state, SOS was intentionally platform agnostic, meaning that it did not describe how to use MV's learning management system specifically. Instead, it focused on strategies for learning in an online environment in general.

It includes five components: a pre-assessment, three interactive content modules, and a post-assessment. MV estimated that it would take approximately 90–120 minutes for a student to complete SOS. The modules include components such as card sorts, self-checks, online teacher videos, and downloadable resources. The three modules are as follows:

1. Online learning basics
2. Skills for online learning
3. Online learning technology

The first module focuses on the differences between online and face-to-face learning. It includes an overview of how online courses work and some basic information related to technology. The second module describes learning and communication strategies. It also describes strategies for time management, organization, and reducing distractions. The third module focuses on specific technology skills, including searching the internet, using communication tools, and managing documents.

In order for us to study SOS as MV would have implemented it in the absence of this research study, students in the treatment group were encouraged but not required to take SOS. This approach was utilized for two reasons. First, SOS was implemented in the manner in which it would have been implemented in the absence of this research study. Requiring SOS would have meant that MV would have needed to institute a process to unenroll students from their online courses if they did not complete SOS, which could have implications for students' credits and grade progression. Second, in the absence of evidence that SOS improved students' outcomes, requiring SOS could have potentially placed an undue burden on students' time. When students were assigned SOS, it appeared as the first "course" for the student in the learning management system, listed above the courses in which the student was enrolled (e.g., algebra, biology, Spanish). Students received initial messages, reminders, and announcements encouraging them to complete SOS prior to starting their online course. Online teachers were blind to assignment, but mentors could see through the learning management system if a student was assigned to SOS. It was important to inform teachers and mentors about the orientation in case questions arose from students. If prompted by students, online teachers and onsite mentors were asked to encourage students who were assigned SOS to complete it.

SOS suffered from low fidelity of implementation; that is, 55% of students assigned SOS completed at least one of the five components. In all, 37% completed all components (see Table 2). Although this is low from the standpoint of an RCT, the fact that over a third of students actually completed a noncompulsory orientation was notable, particularly considering that nearly half of the students in the sample enrolled in their online courses after the official course start date.

[Insert Table 2 here]

Students enrolled in SOS also had access to the BAU supports described below: an introductory unit specific to the course in which they enrolled, an onsite mentor, and access to previous orientation materials.

BAU Supports

Students in the BAU group were not enrolled in SOS and had access to the typical supports for students. The BAU group could also access the previous orientation materials developed in 2000 if they wanted to do so, as these materials were still available on the MV website. Students in both the BAU and treatment groups had an introductory unit in each of their courses. Unlike SOS, the introductory unit focused on the operational aspects of using the learning management system. This included information, for example, about how to upload and download documents and how to submit a post to the discussion board. All students in online courses in Michigan, including those in the treatment and BAU groups for this study, were required to have an onsite mentor at the brick-and-mortar school. An onsite mentor is a school staff person who is responsible for enrolling students in their online course and supporting them throughout the course. In practice, the role of the onsite mentor varies, but the mentor is typically responsible for enrolling students, checking on and supporting their progress, and assigning final grades.

Analytic Approach

In a student-level RCT, the mean outcome between the treatment group and the BAU group constitutes the impact of the treatment. However, this approach to estimating the impact can be compromised in two ways. The first is through chance failure of random assignment resulting in two non-equivalent groups at the time of assignment. The second is attrition, which can occur when students who are randomly assigned in a study are not included when researchers examine the outcome of interest. There is no attrition in this study because the outcome variable does not have a missing value. That is, all students who were randomly assigned had outcomes that fall into one of the three categories described above (i.e., completed the course, did not complete the course, dropped during the grace period). Therefore, we tested baseline equivalence and examined whether there was chance failure of random assignment.

The primary impact estimate for this study is an intent-to-treat estimate. In other words, the impact estimated compares the outcomes for students assigned to the treatment group to the outcome for students assigned to the BAU group. In this context, some individuals who were assigned to the treatment group (i.e., enrolled in SOS) completed it while other students did not complete it.

In the following section, we describe the analytical approach for each of the three research questions, estimating the impact of *enrollment* in SOS on subsequent online course completion, estimating the influence of three potential moderators, and estimating the impact of *completing* SOS on subsequent online course completion. To address the first two research questions, we relied on two types of multilevel regression models for categorical outcomes: a hierarchical multinomial regression model and a hierarchical logistic regression model. We addressed the third research question using an instrumental variable model.

Research Question 1*: *How does Enrollment in an Online Orientation Impact Students' Online Course Outcomes?

For our confirmatory analysis, we used a multinomial regression model because the outcome consisted of these three mutually exclusive and exhaustive categories: (a) the student completed the course; (b) the student did not complete the course, or (c) the student dropped the course during the grace period. It was necessary to cluster the standard errors because teachers exert idiosyncratic effects on student outcomes through several factors, including differences in teaching styles, types and responsiveness to feedback, and amount of synchronous activity. Further, clustering by section also accounted for idiosyncratic effects on the outcome based on the course (e.g., curriculum, subject, instructional design) because sections are clustered within courses. We used the following hierarchical multinomial regression, as well as its variations, for estimating the impact of SOS on the student outcomes:

[Student-Level Model]

$$Log(P\_Complete / P\_NotComplete) = b_{0j\_comp} + b_{1j\_comp}(SOS)_{ij} + \sum b_{mj\_comp}(COV)_{ij}$$

$$Log(P\_DropGrace / P\_NotComplete) = b_{0j\_drop} + b_{1j\_drop}(SOS)_{ij} + \sum b_{mj\_drop}(COV)_{ij}$$

[Section-Level Model]

Model for Intercept

$$b_{0j\_comp} = g_{00\_comp} + \sum g_{0n\_comp}(COV)_{j} + u_{0j\_comp}$$

$$b_{0j\_drop} = g_{00\_drop} + \sum g_{0n\_drop}(COV)_{j} + u_{0j\_drop}$$

Model for Slope b_{1j}

$$b_{1j\_comp} = g_{10\_comp}$$

$b_{1j\_drop} = g_{10\_drop}$

In this model, *P_status* represents the likelihood of a student completing, not completing, or dropping during the grace period. SOS represents assignment to treatment group, and consequently, the estimated impact of it is the coefficient b_{1j}. We used a random intercept model for parsimony. That is, whereas the model for the intercept included the random effect u_{0j} to represent the clustering of students within section, the model for the slope does not. *COV* represents student- or section-level background variables to minimize the imbalance in random assignment and to improve the precision of the impact estimate. We used multinomial hierarchical regression models for the confirmatory analysis.

Although all 1,781 students had data on the outcome variable or course status, not all of them had data on prior achievement and on the attendance rate. One hundred and ninety-two students had missing data on one of the baseline variables. We used the dummy-variable adjustment method for missing covariates because this method does not lead to bias in the impact estimates in RCTs (Puma et al., 2009).

Sensitivity Analysis. We also analyzed the impact of SOS on course outcomes with a logistic regression model as an alternative to multinomial regression. The three outcomes (completing the course, not completing the course, dropping the course during the grace period) have a structure of two successive binary outcomes. First, a student either drops the course during the grace period or continues in the course. Provided that a student continued in the course, then the student will either complete or not complete the course at the end of the term. Conceptualizing the three outcomes this way would unpack the one multinomial outcome into two binary sequential outcomes. Specifically, we performed a set of two hierarchical logistic regressions to estimate the impact of orientation on (a) dropping the course during the grace period as opposed to continuing in the course, and (b) completing the course or not for those who did not drop during the grace period. We used the following hierarchical logistic regression as well as its variations:

[Student-Level Model]

$$Log(P / (1 - P)) = b_{0j} + b_{1j}(SOS)_{ij} + \sum b_{mj}(COV)_{ij}$$

[Section-Level Model]

Model for Intercept

$$b_{0j} = g_{00} + \sum g_{0n}(COV)_j + u_{0j}$$

Model for Slope b_{1j}

$$b_{1j} = g_{10}$$

In this model, *P* first represents the likelihood of a student dropping during the grace period and then represents the likelihood of the student completing the course. *SOS* is a binary variable representing assignment to SOS or to BAU, and consequently the estimated impact of it is the coefficient b_{1j}. We used a random intercept model for parsimony. That is, whereas the model for the intercept included the random effect u_{0j} to represent the clustering of students within section, the model for the slope does not. *COV* represents student- or section-level background variables to minimize the imbalance in random assignment and to improve the precision of the impact estimate. The following set of covariates were used for Research Question 1: (a) prior eighth-grade scaled scores in mathematics and ELA, (b) attendance rate from the previous year, and (c) enrollment in core courses.

As a second sensitivity analysis, we ran the multinomial regression model on the full sample of 8,256 students. Because we were not able to merge these data with the administrative and assessment data from MDE, the only covariate in the model was core course and the model could not be limited to first-time online students.

Research Question 2: Does Type of Course, Timing of Enrollment, or Grade Level Moderate the Relationship Between Enrollment in an Online Orientation and Students' Online Course Outcomes?

This study examined three potential moderators as exploratory analyses: type of course, timing of enrollment, and grade level. Type of course was a binary variable equal to 1 if the student enrolled in a core course or 0 if the student enrolled in a non-core course. Core course was included as the moderator, as we hypothesized that students may treat core and non-core courses differently, which would affect the outcome (main effect) as well as the degree to which SOS exerts its impact on the outcome (moderator effect).

Timing of enrollment was also operationalized as a binary variable equal to 1 if the student enrolled prior to the course start date (on-time) and equal to 0 if they did so on or after the course start date (late). Many students enroll after the online course's official start date because they decide to take an online course after they start school. This decision may be because of scheduling conflicts, a desire to take a course not available in their school, or to make up credits for courses that they did not pass. Further, school staff members often enroll students in batches rather than individually, suggesting that there may be a lag between when students decide to take an online course and when they are enrolled in that course. We hypothesized that students who enrolled on time may do better in their online courses than students who enrolled late and that the timing of enrollment may also influence the extent to which SOS had an impact on course outcomes.

Grade level served as the third moderator variable because we hypothesized that SOS may impact students differently based on their grades. Students who were earlier in their high school careers may benefit more from SOS because they are less familiar with using technology in learning. On the other hand, it could be that the 12th-graders enrolled in online courses would benefit more from SOS because they may be taking the course to fulfill the online learning experience graduate requirement, rather than from an interest in taking an online course or the specific course in which they are enrolled. Given that 45% of the sample was in Grade 12 and an online learning experience is a graduation requirement, we operationalized grade level as a binary variable equal to 1 if the student was in Grade 12 and equal to 0 if the student was in Grade 9, 10, or 11.

To address Research Question 2, we ran three separate regressions utilizing the hierarchical multinomial regression model from Research Question 1 and adding each of the following as a moderator in the model, which involved adding a term for the moderator main effect as well as a term for moderator-by-SOS interaction: (a) enrollment in core courses, (b) on-time enrollment, and (c) Grade 12. We used eighth-grade scaled scores in mathematics and ELA, prior attendance rate, and enrollment into core courses as covariates.

Sensitivity Analysis. As in Research Question 1, we also conducted the moderator analyses using logistic regression models as an alternative to multinomial regressions.

Research Question 3: *Are Students who Complete the Orientation More Likely to Complete their Online Courses?*

As noted above, fidelity of implementation was low, as 37% of students completed all components (see Table 2). As the intent-to-treat estimates the treatment impact using assignment to the treatment, not the receipt of the treatment, this low level of fidelity of implementation dilutes the estimate of potential impact of the treatment. Treatment-on-the-treated analysis solves this problem in inference, by estimating the impact based on the receipt of treatment. However, students choose whether to complete SOS. To address selection bias, we used an instrumental variable (IV) strategy (Angrist et al., 1996), in which we predicted, in the first stage, the likelihood that a student completed SOS given their treatment assignment.

$$\textit{Completion of SOS Components}_i = a_0 + a_1(\textit{Assignment to SOS})_i + \sum a_m(\textit{COV})_i + e_i$$

That prediction was then used rather than treatment status in the second stage to estimate the impact of the treatment-on-the-treated. We performed a set of two IV probit models and estimated the impact of completing all components of SOS on (a) dropping the course during the grace period as opposed to continuing in the course, and (b) completing the course as opposed to not completing the course.

$$Y_i = b_0 + b_1(\textit{Predicted Completion of SOS Components})_i + \sum b_m(\textit{COV})_i + u_i$$

As students were nested within sections and teachers, the standard error was cluster-adjusted for section. Because the assignment to SOS was done randomly, assignment to SOS qualified as the perfect instrument for removing selection bias, enabling the unbiased estimate of impact on the treated. In this study, the only causal path through which the assignment to the SOS could impact online course outcomes is through SOS.

Baseline Equivalence

We examined baseline equivalence to identify potential pre-intervention measures where random assignment may not have been as successful as intended by the design. Specifically, we used *t*-tests for independent samples to determine whether significant differences existed between the treatment and BAU on the three baseline measures: eighth-grade mathematics scale scores and eighth-grade ELA scale scores from the statewide standardized assessment, as well as prior year attendance rate. We then estimated standardized effect sizes using Hedges's *g* and compared them against the WWC standard for baseline equivalence (Table 3). Because the effect sizes for eighth-grade mathematics scale score (0.06) and prior year attendance rate (0.10) were greater than 0.05, we included those variables as covariates in the models.

[Insert Table 3 here]

We further compared the characteristics of those in the treatment and BAU conditions to detect whether there was any imbalance in the characteristics of students or the types of courses in which they enrolled. Specifically, we used chi-square tests of association and *t*-tests for independent samples to determine whether significant differences existed between the treatment and BAU for several student-level variables, including gender, race, grade, Individualized Education Program status, and indicators for limited English proficient and economic disadvantage. We also examined differences in the proportion of students enrolled in core courses, specific course subjects, and the timing of enrollment (i.e., prior to the course start date). The results of this analysis are reported in Tables 4 and 5. Based on *t*-tests for continuous variables and chi-square tests for categorical variables, there were no significant differences in the students in the treatment and BAU groups.

[Insert Tables 4 and 5 here]

Results

The online course outcomes for students assigned SOS and students who received BAU supports were similar. In both groups, approximately 75% of students completed their online courses (i.e., earned at least 60% of the course points), 10% dropped during the grace period, and 15% did not complete their course or dropped it after the grace period (Figure 1).

[Insert Figure 1 here]

Research Question 1: How does Enrollment in an Online Orientation Impact Students' Online Course Outcomes?

For our confirmatory analysis, the impact of SOS on the outcome (completing the course, not completing the course, dropping during the grace period) was estimated, with prior academic achievement (eighth-grade mathematics and ELA scale scores), prior year attendance rate (2017/18), and enrollment in a core course used as covariates. Table 6 includes relative risk ratios (RRR), where RRR expresses the effect of each variable in terms of its ability to alter the ratio of one outcome occurring instead of the referent outcome. The referent outcome here is not completing the course. RRR has the expected value of 1 when the variable has no effect. An RRR larger than 1 signifies that the variable increases the relative risk of one outcome as opposed to the referent outcome; whereas an RRR value of smaller than 1 signifies that the variable decreases the relative risk. For example, the RRR of 1.08 for treatment means that enrollment in SOS improved the relative risk of completing the course as opposed to dropping the course by a factor of 1.08, which is not significant.

With an RRR of 1.08, we did not find an impact of SOS on the relative risk of completing the course as opposed to dropping the course. Further, there was no evidence of an impact of SOS on the relative risk of dropping during the grace period as opposed to not completing the course. Meanwhile, prior achievement and prior year attendance rate were both positively associated with completing the course as opposed to not completing the course. Enrolling in a core course, on the other hand, was associated with a lower relative risk of completing the course compared to not completing the course. When we examined the relative risk of dropping during the grace period as opposed to not completing the course, none of the covariates had significant RRRs.

[Insert Table 6 here]

Sensitivity Analysis

To verify the finding based on the multinomial hierarchical regression model analysis, we ran a set of two hierarchical logistic regressions for the main model. Like the confirmatory analysis, we did not find an impact of SOS on dropping the course during the grace period, nor on completing the course. Both prior achievement and prior attendance rate were significantly associated with a higher chance of completing the course, if the students did not drop the course during the grace period (Appendix, Table A2).

In addition, we ran the multinomial regression model on the full sample of over 8,000 students. Like the confirmatory analysis with the matched sample, no significant differences were found in course outcomes between students enrolled in SOS and students with BAU supports (Appendix, Table A3).

Research Question 2: Does Type of Course, Timing of Enrollment, or Grade Level Moderate the Relationship Between Enrollment in an Online Orientation and Students' Online Course Outcomes?

Of the three moderator analyses we conducted, the only variable that had a moderating effect was the indicator for whether a student enrolled on time (Model 2; Table 7). Neither the indicator for enrollment into a core course (Model 1) nor the indicator for Grade 12 (Model 3) were significant. For students who enrolled on time, the RRR of dropping during the grace period as opposed to not completing the course was positive, at 1.76; for late enrollers, this RRR was negative, at 0.72. This difference was significant, which suggests that students who enroll on time, and potentially had the opportunity to take SOS prior to starting their course, were more likely to drop during the grace period than to drop after the grace period or fail the course. The reverse was true for those who enrolled late.

[Insert Table 7 here]

When we examined the data descriptively, the percentage of students who completed their online course was similar between those in the treatment and BAU groups, regardless of whether they were enrolled on time or late. However, for those who enrolled on time, there were differences between the treatment and BAU groups in the percentages who dropped during the grace period (11% compared to 8%) and did not complete the course (11% compared to 13%). The opposite pattern emerged for late enrollers. For late enrollers, a lower percentage of students assigned SOS dropped during the grace period, and a higher percentage did not complete the course compared to students in the BAU group (Figure 2). Not surprisingly, students who enrolled on time, regardless of their treatment status, were significantly more likely to complete the course as opposed to not completing it, compared to late enrollers.

[Insert Figure 2 here]

Sensitivity Analysis

The sensitivity analysis using logistic regressions also replicated the results of the exploratory moderator analysis. On-time enrollment showed a near-significant moderator effect on dropping during the grace period. Whereas assignment to SOS decreased the odds of dropping during the grace period by 0.74 for late enrollers, it increased the odds by 1.39 for on-time enrollers (Appendix, Table A2).

Research Question 3: Are Students who *Complete* the Orientation More Likely to Complete their Online Courses?

We first descriptively compared the characteristics of students who completed SOS to students who did not complete SOS and found that students who completed SOS had higher eighth-grade mathematics and ELA scores, were more likely to be female, and were less likely to be economically disadvantaged than those who did not complete SOS (Table 8). Further, they were more likely to be enrolled in a core course and to have enrolled on time. Many of these characteristics also predicted students' online course outcomes. There may be other unobserved factors, such as a reason for taking the online course, that could impact both students' likelihood of completing SOS and their course outcome.

[Insert Table 8 here]

Thus, we conducted two exploratory treatment-on-the-treated analyses using IV models to estimate the impact of completing SOS on (a) dropping the online course during the grace period as opposed to continuing in the course, and (b) completing the course as opposed to not completing the course for students who continued in the course after the grace period. For both models, the first-stage equations indicated that treatment status predicted whether a student completed all components of SOS. Although the result is not significant, students who completed SOS had a greater probability of completing the course compared to students who did not complete SOS (Appendix, Table A4). The lack of significance may be on account of inefficiency of instrumental variable models and the small sample size. When we examined students who did complete the course, their scores on both the pre- and post-assessment increased by 2 points on average (6.6 to 8.6 out of 10; t = 8.41), further suggesting that SOS did increase students' preparedness to learn online.

Discussion

We did not find evidence that being assigned SOS improved novice online learners' outcomes in their online courses. However, this study examined only one orientation in a particular setting. Given the widespread use of orientations and the opportunity cost of students' time, particularly for late enrollers, the results raise important questions about the utility of orientations and what type of orientation is most effective. In particular, it points to the need for further research on the implementation, design, and content choices related to orientations. It also necessitates further discussion of what supports high school students may need in addition to an orientation to be successful in online courses.

Implementation of Orientations

With a little more than a third of students completing SOS, this study raised questions about the implementation of SOS and orientations more generally. Key implementation questions include whether the orientation is required, when it is provided to students, and whether it is supplemented by a face-to-face or synchronous component. These questions warrant both further research and intentional decision-making by online programs as the answers may influence outcomes for students.

SOS was both not required and asynchronous. As such, students could begin their courses without completing SOS and did not have to engage synchronously with their mentor or an online learning program staff member prior to moving forward with their course content. Making an orientation required may help reach students who are most at risk of not completing their courses. At the same time, implementing a synchronous component with a mentor or program staff person may establish a connection to a supportive adult from the start. However, the decision about requiring an orientation or scheduling a synchronous component must also consider the program capacity and potential negative consequences for students, such as not having access to a course needed to graduate or the potential to negatively influence their outcomes if they are enrolled late in the semester. In the latter case, our findings indicate that being assigned SOS had a potentially negative impact on late enrollers compared to on-time enrollers. This may because the opportunity cost to complete the orientation is too high; the time spent on the orientation could have been used to do their online coursework. It could also be that there are some other characteristics of late enrollers that mediate the effectiveness of the orientation. These decisions regarding implementation may affect the number of students who complete the orientation and the level of students' preparedness for online learning.

Content and Design of Orientations

The orientation studied purposefully did not focus on how to use MV's specific learning management system. Rather, the platform-agnostic orientation focused on learning online more generally, including time management and identifying who to go to with questions. This focus on online learning more generally is similar to study skills or bridge programs to support the transition from high school to college (e.g., Jordan, Parker, Li, & Onwuegbuzie1, 2015; Rutschow, Cullinan, & Welbeck, 2012), but different from orientations provided by other online learning programs described in the literature review, which also focused on the practical aspects of learning in an online environment. The decisions about content and design may influence the number of students who complete the orientation and the level of students' preparedness for online learning. Qualitative research on students' perceptions of and feedback on orientations, including the one studied here, could support online programs in making decisions about content and design, which may better engage students.

More Research is Needed to Modify Standards for Online Learning

The current standards for online programs to offer “an orientation for taking an online course” should be revised to be more specific, as more research emerges on what makes an orientation effective and what additional student supports may compliment an orientation. To support revisions to these guidelines, additional research could compare different approaches to orienting students to understand what improves students’ online course outcomes. For example, a future study could determine whether orientations should focus more on self-regulation and time-management skills or on the practical aspects of engaging in an online course, such as uploading documents and posting to discussion boards. Additional studies about the roles of mentors or online program staff in orientating students could be useful.

Orientations as One Component of a System of Supports

An asynchronous one-time two-hour orientation may not be enough to solve the completion problem that plagues online courses. It may be one component of a menu supports for students to be successful. These systems of support may include interactions between students and online teachers, mentors, parents, and peers throughout the online course, not solely at the start (Borup et al., 2019; Borup et al., 2014; Harms et al., 2006). There is correlational and experimental evidence to suggest that mentors—brick-and-mortar school staff assigned to assist online students—may influence student completion rates and learning outcomes (Borup & Stimson, 2017; Hannum et al., 2008; Irvin et al., 2009; Taylor et al., 2016). Future research could examine whether orientations along with a more robust system of supports have a positive impact on student outcomes.

Considerations for Timing of Enrollment

Regardless of treatment status, students who enrolled in their online courses on time were more likely to complete their online courses. This finding is critical to thinking about how to help students succeed in their courses; this study and others focused on supporting students or on comparing outcomes to face-to-face have not raised the question about whether timing of enrollment matters. While not a causal claim, this study indicates that timing of enrollment potentially has a large influence on student success and should be considered for both future research and for practice.

Timing of enrollment can be affected by several factors. In most schools, a school staff member is responsible for enrolling students in online courses, and they may not do so until after the school year has started. This may be because of changes in students' schedules or courses, a desire to enroll students in batches rather individually, or because of the "anytime anyplace" philosophy of online courses. Schools and online programs should consider how long after the official start date students can enroll in an online course, and if they do enroll in an online course late, whether to offer an orientation.

Students who enrolled on time and were assigned SOS were more likely to drop their online course during the grace period than to not complete their courses, and the reverse was true for students who enrolled late. An online program or school may see this increased probability of dropping during the grace period as a positive outcome if the goal of an orientation is to screen out students who may not be successful in an online environment. However, if the goal is to prepare *all* students to be successful in their online course, it may be that more supports are necessary for some students. Online programs should be specific about the goals of their orientations and future research could examine the effectiveness of orientations in relation to the specified goal.

Limitations

This study examined one orientation, SOS, implemented in a specific way and thus findings should not be generalized to all orientations. Further, there was low adherence to SOS, with 37% of students in the treatment group completing all components of SOS. However, the results of this study should not be discounted because of this low adherence, as SOS was implemented as it would have been without the research study in place.

Additionally, the sample included students who take courses with MV, who have higher online course completion rates, are more likely to be proficient on state assessments, and are less likely to be economically disadvantaged compared to students in Michigan who take online courses through other programs (Freidhoff, 2019). Further, the types of courses and timing of enrollment for students who could be matched between MV and MDE differed, suggesting that the results should not be generalized to all students in Michigan. Further research is needed to understand whether SOS impacts outcomes for students with different characteristics.

Conclusion

This study contributes to the limited body of rigorous research on factors that support high school students to be successful in online courses. Other experimental studies have either compared face-to-face to online instruction or investigated features of course design and online instruction as they relate to student outcomes, such as the use of problem-solving question prompts or types of feedback through a web-based tutor (Huang et al., 2016, McGuire et al., 2017, Meyer et al., 2010). The null findings for this orientation suggest that more research needs to be done on orienting or onboarding secondary students to online courses. Given the number of students engaging in online courses, especially as a result of the COVID-19 pandemic, there is a need to understand whether and how to design and implement orientations to improve outcomes for students. This need is particularly important, as this study provides some evidence that an orientation may screen out some students rather than prepare them to be successful in an online course.

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Table 1

Sample Descriptive Statistics

	Study Sample	
	N	Percent
Course characteristics		
Core course	1,271	71.4
Course subject area		
Math and science	286	16.1
World language	549	30.8
English	101	5.7
Other	845	47.5
Enrolled on time	932	52.3
Student characteristics		
Individualized Education Program	71	4.0
Limited English proficient	11	0.6
Economically disadvantaged	477	26.8
Female	837	47.0
Race		
White	1,498	84.1
African American	56	3.1
Hispanic	66	3.7
Asian	79	4.4
Other	82	4.6
Grade level		
9	189	10.6
10	296	16.6
11	487	27.3
12	809	45.4

Note. *N* = 1,781.

Table 2

Fidelity of Implementation

	N	% of students
Completed at least 1 module	500	55.0
Completed all components	340	37.4
Components		
Pre-assessment	458	50.3
Module 1	414	45.5
Module 2	379	41.7
Module 3	367	40.3
Post-assessment	391	43.0

Note. n = 910.

Table 3

Baseline Equivalence

Baseline covariate	BAU *M*	Treatment *M*	Test statistic[a]	*p*	Hedges's g	*N*
Grade 8 mathematics scale score	1801.9	1800.5	1.202	.230	0.06	1,592
Grade 8 English language arts scale score	1810.6	1810.3	0.299	.765	0.02	1,592
Prior year attendance rate	0.95	0.94	2.093*	.037	0.10	1,706

Note. [a] Test statistic is produced from an independent sample *t*-test.

*$p < .05$, **$p < .01$, ***$p < .001$

Table 4

Random Assignment Check Using Observed Student Characteristics

Student characteristic	BAU %	Treatment %	Test statistic[a]	p
Individualized Education Program	4.1	3.9	0.096	.757
Limited English proficient	0.8	0.4	0.961	.327
Economically disadvantaged	27.2	26.4	0.159	.690
Female	46.4	47.6	0.257	.612
Race/ethnicity			4.148	.528
White	83.1	85.1		
African American	3.2	3.1		
Hispanic	3.3	4.1		
Asian	5.2	3.7		
Other	5.2	4.1		
Grade			4.946	.293
9	10.7	10.6		
10	15.7	17.5		
11	26.0	28.7		
12	47.8	43.2		

Note. N = 1,781.

[a] Test statistic is produced from a chi-square test of association.

Table 5

Random Assignment Check Using Observed Course Characteristics

	Control %	Treatment %	Test statistic[a]	*p*
Core course	70.0	72.6	1.476	.224
Course subject area			4.330	.228
Mathematics and science	16.2	15.9		
World languages	28.6	33.0		
English	6.1	5.3		
Other	49.1	45.8		
Enrolled on time	52.7	52.0	0.093	.761

Note. $N = 1,781$.

[a] Test statistic is produced from a chi-square test of association.

Table 6

Intent-to-Treat Analysis: Causal Effects of Strategies for Online Success on Course Outcome

	Relative risk ratio	Standard error
Completed the course		
Treatment	1.08	.15
Core course	0.65*	.12
Grade 8 mathematics scale score	1.02**	.01
Grade 8 English language arts scale score	1.02**	.005
Prior year attendance rate	56.75**	76.78
Constant	0.17	.22
Dropped during the grace period		
Treatment	1.09	.22
Core course	0.98	.26
Grade 8 mathematics scale score	1.00	.01
Grade 8 English language arts scale score	1.00	.01
Prior year attendance rate	2.22	.52
Constant	0.33	.23
Model statistics		
N	1,781	
Wald chi(2)	108.58	
Pseudo R^2	.07	

Note. Referent outcome is "did not complete the course". The model also included dummy variables for missing data on Grade 8 mathematics scale score, Grade 8 English language arts scale score, and prior year attendance rate.

$^{**}p < .01$ $^{*}p < .05$ $^{+}p < .1$

Table 7

Intent-to-Treat Moderator Analysis

	Model 1		Model 2		Model 3	
	RRR	*SE*	RRR	*SE*	RRR	*SE*
Completed the course						
Treatment	0.83	.22	0.91	.17	1.17	.21
Core course	0.54*	.13	0.61*	.12	0.66*	.13
Grade 8 mathematics scale score	1.02**	.01	1.02**	.01	1.02***	.01
Grade 8 English language arts scale score	1.02**	.005	1.02**	.005	1.02**	.005
Prior year attendance rate	58.99**	79.26	46.48**	60.82	41.94**	53.48
Grade 12					1.65*	.37
Enrolled on time			1.57*	.35	1.95**	.36
Treatment x core course	0.54	.13				
Treatment x enrolled on time			1.49	.48		
Treatment x Grade 12					0.82	.24
Constant	0.18	.24	0.17	.21	0.13*	.16
Dropped during the grace period						
Treatment	1.21	.51	0.72	.18	1.16	.30
Core course	1.07	.40	0.93	.26	1.02	.27
Grade 8 mathematics scale score	1.00	.01	1.00	.01	1.01	.01
Grade 8 English language arts scale score	1.00	.01	1.01	.01	1.01	.01
Prior year attendance rate	2.18	1.50	2.06	1.42	1.92	1.31
Grade 12					1.60	.49
Enrolled on time			0.96	.30	1.58^{+}	.39

Treatment x core course	0.87	.42				
Treatment x enrolled on time			2.46*	1.06		
Treatment x Grade 12					0.84	.33
Constant	0.31	.23	0.37	.27	0.24*	.17
Model statistics						
N	1,781		1,781		1,780	
Wald chi(2)	116.62		119.53		120.86	
Pseudo R^2	.07		.08		.08	

Note. RRR = Relative risk ratio; *SE* = Standard error. Referent outcome is “did not complete the course”. The model also included dummy variables for missing data on Grade 8 mathematics scale score, Grade 8 English language arts scale score, and prior year attendance rate.

**p < .01 *p < .05 $^{+}$p < .1

Table 8

Student Characteristics by Strategies for Online Success (SOS) Completion Status

	Completed SOS	Did not complete SOS	Test statistic[a]	*p*	*N*
Grade 8 mathematics scale score	1804	1798	3.570**	.00	811
Grade 8 English language arts scale score	1814	1808	3.425**	.00	812
Prior year attendance rate	94%	94%	0.655	.51	868
Individualized Education Program	3%	4%	1.202	.27	910
Limited English proficient	0%	1%	2.397	.12	910
Economically disadvantaged	21%	30%	9.356*	.01	910
Female	53%	45%	5.582*	.02	910
Grade			4.207	.38	910
9	10%	11%			
10	16%	18%			
11	27%	30%			
12	46%	41%			
Core course	78%	70%	6.854*	.01	910

Note. Test statistic was calculated from a chi-square test of association for all variables except for Grade 8 mathematics and English language arts scale scores, and prior year attendance rate. For these three variables, the test statistic was produced from an independent sample *t*-test.

$^{**}p < .01$ $^{*}p < .05$ $^{+}p < .1$

Figure 1

Course Outcomes for Students Assigned Strategies for Online Success (SOS) Compared to Business-as-Usual

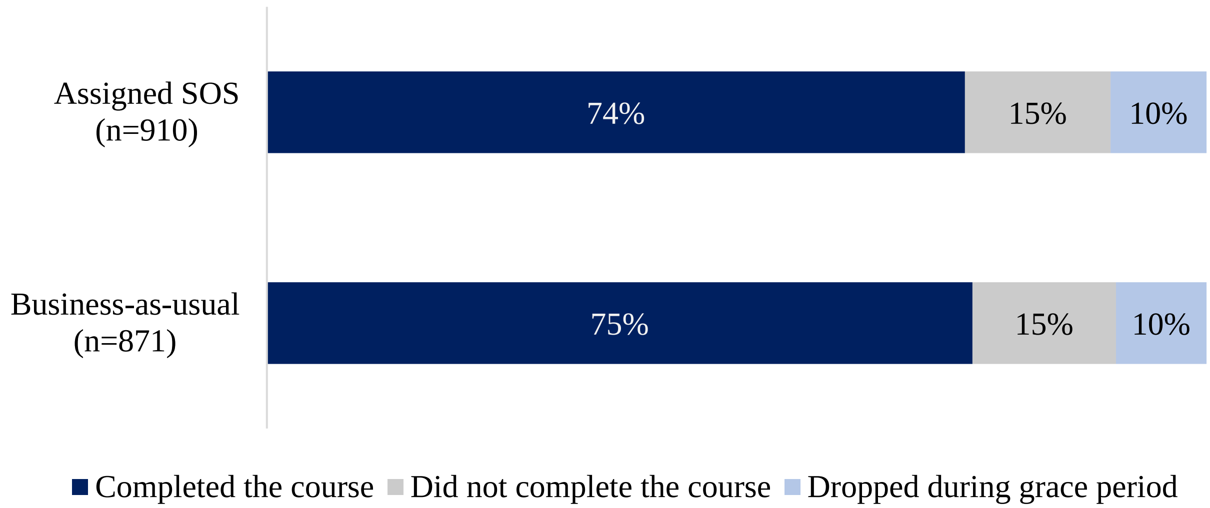
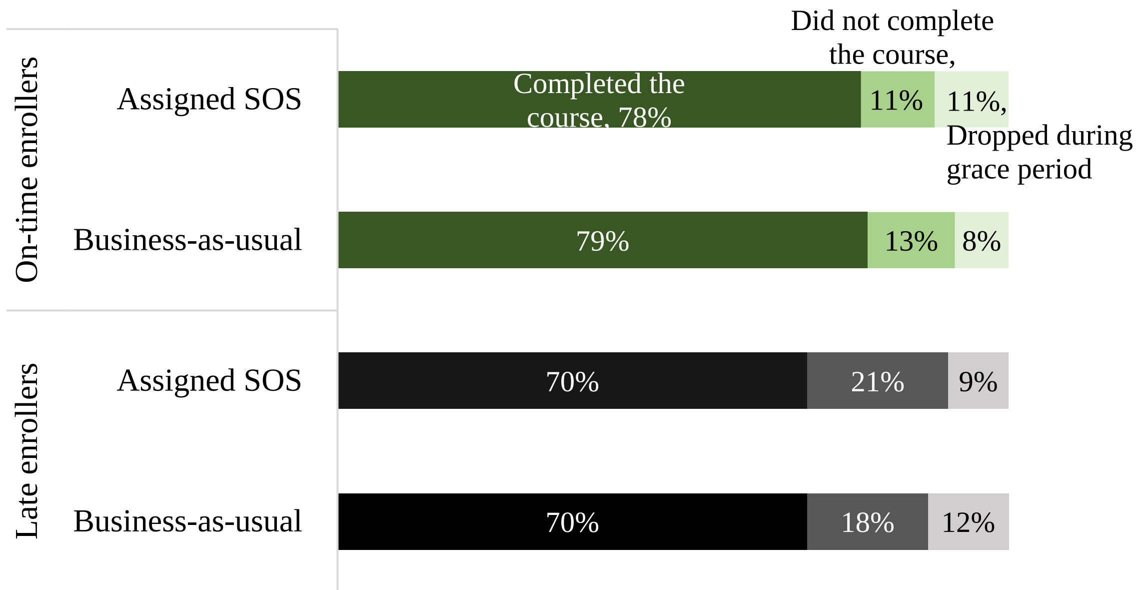


Figure 2

Course Outcomes by Enrollment Timing and Random Assignment into Strategies for Online Success (SOS) and Business-as-Usual



Appendix

Supplementary Tables

Table A1

Tests of Differences Between Matched and Unmatched Samples

Characteristic	Unmatched sample	Matched sample	Test statistic[a]	*p value*	*Effect size*
Treatment	48.2%	50.5%	3.502[+]	.061	0.06
Core course	73.8%	72.1%	2.307	.129	–0.05
Subject area			10.950*	.012	
Mathematics and science	15.9%	16.2%			0.01
World languages	33.4%	31.2%			–0.06
English	5.2%	6.8%			0.17
Other	45.5%	45.8%			0.01
On-time enrollment	45.7%	51.4%	22.887**	.000	0.14
Completed all sections of Strategies for Online Success	32.0%	37.5%	11.554**	.001	0.15
N size	5,740	2,516	--	--	

Note. Test statistic is calculated from chi-square test of association for all variables except for course grade, for which the test statistic is produced from an independent sample *t*-test.

***p* < .01 **p* < .05 +*p* < .1

Table A2

Sensitivity Analysis: Logistic Regressions

	Main analysis				Moderator analysis			
	Dropped during the grace period		Did not complete the course		Dropped during the grace period		Did not complete the course	
	Odds ratio	Standard error	Odds ratio	Standard error	Odds ratio	Standard error	Odds ratio	Standard error
Treatment	1.02	.169	0.96	.147	0.74	.176	1.11	.232
Core course	1.46	.314	1.60*	.336	1.45	.313	1.68*	.351
Grade 8 mathematics scale score	0.99	.005	0.98**	.005	0.99	.005	0.98**	.005
Grade 8 English language arts scale score	1.00	.005	0.98**	.005	1.00	.005	0.98**	.005
Prior year attendance rate	0.28^{+}	.207	0.02**	.017	0.28^{+}	.209	0.02**	.021
Enrolled on time					0.65^{+}	.161	0.60^{+}	.137
Treatment x enrolled on time					1.87^{+}	.627	0.69	.215
Constant	0.23*	.170	4.08^{+}	3.44	0.28^{+}	.212	4.5	3.58
Model statistics								
N size	1,781		1,604		1,781		1,604	
Wald chi(2)	20.99**		104.88**		24.46**		118.43**	

Note. The model also included dummy variables for missing data on Grade 8 mathematics scale score, Grade 8 English language arts scale score, and prior year attendance rate.

**$p < .01$ *$p < .05$ +$p < .1$

Table A3

Sensitivity Analysis: Causal Effects of Strategies for Online Success on Course Outcome With Full Sample

	Relative risk ratio	Standard error
Did not complete the course (base = completed)		
Treatment	1.09	.69
Core course	1.64**	.19
Constant	0.14**	.01
Dropped during the grace period		
Treatment	1.16	.09
Core course	1.13	.12
Constant	0.11***	.01
Model statistics		
N	8,256	
Wald chi(2)	23.99	
Pseudo R^2	.004	

Note. Referent outcome is "did not complete the course."

**$p < .01$ *$p < .05$ $^{+}p < .1$

Table A4

Treatment-on-the-Treated: Instrumental Variable Probit Model Results

	Dropped during the grace period		Did not complete the course	
	Coefficient	Standard error	Coefficient	Standard error
Completed all SOS sections	–0.03	.23	–0.17	.20
Core course	0.17+	.10	0.24*	.10
Grade 8 mathematics scale score	0.004	.003	–0.01**	.003
Grade 8 English language arts scale score	–0.002	.003	–0.01**	.002
Prior year attendance rate	–0.78*	.40	–2.24**	.58
Constant	–0.71*	.39	0.94*	.56
First-stage estimates of SOS completion				
Treatment	0.37**	.02	0.39**	.02
Core course	0.05*	.02	0.04*	.02
Grade 8 mathematics scale score	0.001	.001	0.001	.001
Grade 8 English language arts scale score	0.001	.001	0.001	.001
Prior year attendance rate	0.03	.11	–0.02	.13
Constant	–0.06	.11	–0.01	.13
Model statistics				
N size	1,781		1,604	
Wald chi(2)	20.72**		95.93	
Wald test of exogeneity	2.32		1.07	
Wald test of exogeneity *p* value	0.12		0.30	

Note. SOS = Strategies for Online Success. The model also included dummy variables for missing data on Grade 8 mathematics scale score, Grade 8 English language arts scale score, and prior year attendance rate.

**$p < .01$ *$p < .05$ +$p < .1$

[i] Based on the National Assessment of Educational Progress (2015), an estimated 12% of 12th-grade students took an online mathematics course for credit and 19% took an online English course for credit. With approximately 3.5 million 12th-grade public school students (U.S. Department of Education, 2015), these findings suggest that an estimated 420,000 public school 12th-grade students took an online mathematics course and 665,000 students took an online English course.