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Burns, Kathleen; Duncan, Mimi; Sweeney, Donald C. II; North, Jeremy W.; and Ellegood, William A., "A Longitudinal Comparison of Course Delivery Modes of an Introductory Information Systems Course and Their Impact on a Subsequent Information Systems Course" (2013). *College of Business Administration Faculty Works*. 17.
Available at: https://irl.umsl.edu/business-faculty/17

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A Longitudinal Comparison of Course Delivery Modes of an Introductory Information Systems Course and Their Impact on a Subsequent Information Systems Course

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Abstract

This paper presents a robust longitudinal comparison of student learning in face-to-face (F2F), online, and hybrid delivery methods of a two-course sequence in information systems, required of all business majors, at a Midwestern land grant university. Student learning was evaluated by delivery method in the introductory first class of the sequence, using an ordered probit regression model of letter grade earned controlling for the effects of other possible explanatory variables. Cumulative grade point average was found to be a consistent determinant in student success, and students were found to have significantly better learning outcomes, as expressed through course grades, in the F2F delivery mode for the introductory class. Student grades were then evaluated in the next, more advanced information systems course, using a second ordered probit regression model. The results indicated that mode of delivery, online or F2F, for the more advanced course had no significant impact on student grades for that course, but students who had enrolled in the online and hybrid delivery modes in the first course of the sequence performed significantly better, as measured by course grade, in the more advanced course regardless of delivery mode.

Keywords: delivery methods, information systems education, business education

Introduction

Technology has begun to permeate courses across the higher education sector (Herman & Bannister; 2007; Kury, Jones, Arney, & Lovett, 2007; Ryabov, 2012). Many university administrators perceive online courses as possible solutions to budgetary constraints on their campuses and actively encourage faculty to employ this delivery method in either new or redesigned courses.(Wagner, Garippo, & Lovaas, 2011). While these course offerings may be seen as economic solutions to budget difficulties, for a complete evaluation of the integration of online technologies into content delivery, it is essential to investigate the student learning outcomes in these new technology-based course designs, which can run the gamut from offering all content wholly online to offering just a small portion of the content online.

The impetus of this study was the consequence of two of the authors being awarded a grant by the administration of their research institution in the Fall 2009 semester to create an online version of an existing introductory business course. The grant allowed the researchers to work collaboratively to convert Computers and Information Systems (IS100), a required course for all business majors with all sections meeting in traditional face-to-face (F2F) classrooms, to a course that offered content entirely online.

During the initial phase of implementation, there were two delivery modes used at the institution for delivery of IS100, online and F2F, which ran simultaneously for one full academic year beginning in the Fall 2010 semester. Preliminary data collected at that time showed little differential impact on student learning based on delivery mode. However, the instructor-author desired more F2F time with students than was afforded by the online delivery mode and began looking for a delivery model that would incorporate the best of both worlds as described by Dziuban, Hartman, and Moskal (2004).

In Fall 2011, a state-funded redesign initiative promoted by the National Center for Academic Transformation (NCAT) (http://www.thencat.org/) permitted the development of a third, hybrid section of IS100. The hybrid design in this study is consistent with the model discussed earlier by Kaleta, Garnham, and Aycock (2005) as well as the NCAT-defined replacement model. NCAT (2005, para. 1) describes the replacement model as one that:

- Reduces the number of in-class meetings but does not eliminate all in-class meetings.
- Replaces (rather than supplements) some in-class time with online, interactive learning activities.
- Gives careful consideration to why (and how often) classes need to meet face-to-face.
- Assumes that certain activities can be better accomplished online—individually or in small groups—than in a F2F class.
- May keep remaining in-class activities more or less the same.

- May make significant changes in remaining in-class meetings.
- May schedule out-of-class activities in 24*7 computer labs or totally online so that students can participate anytime, anywhere.

Constructing quality hybrid courses takes time and detailed planning (Rust, 2011). When IS100 was selected as one of the courses that would be developed as part of the statewide NCAT initiative, the instructor was able to work with an experienced instructional designer to develop a hybrid version that would maximize the available technology, as well as the best methodologies of the F2F sections. The goal of the hybrid sections was "to join the best features of in-class teaching with the best features of online learning to promote active independent learning and to reduce class seat-time" (Kaleta, Garnham, & Aycock, 2005, p. 1). The pilot sections of the hybrid model of IS100 were used in this study.

In all versions of IS100, a robust learning management system (LMS) was employed. The LMS allowed for all assignments, discussions, course resources, and assessments to be easily accessed by the students online. A custom portal for use by the instructor and students was designed for this course by the publisher of the texts and held quick links to glossaries, files, and other resources. For this course all assignments, lessons, and exams were created by the instructor and were the same for all sections.

Both courses involved in this study are required of all business majors. The introductory course, IS100, was the initial focus of the study as the researchers had control of all aspects of the course. It was also one of several courses that could be taken by any student to meet a skill goal within the general education requirements under Information Management at this research institution. The breakdown of students taking IS100 was typically 70% business and 30% non-business majors. Until 2010, this course was offered exclusively in F2F delivery mode and had total enrollment numbers of approximately 600 students annually.

To evaluate the potential longitudinal learning impacts for students of the three IS100 delivery modes, IS100 students' subsequent performances in *Concepts and Applications* (IS200), also a required course for business majors with IS100 as a prerequisite, was added as a focus of this study. IS200 was already available in F2F and online formats predating the development of online content for IS100. However, unlike IS100, the researchers were not a part of the development of the curriculum for IS200 in either mode of delivery, and different instructors taught separate sections of the class.

Literature Survey

Since the advent of online learning there have been a multitude of studies comparing and measuring the effectiveness of online course delivery, and more recently hybrid courses, to F2F courses. Many of these studies found little to no significant differences among delivery modes (Herman & Bannister, 2007; Wagner et al., 2011).

Some studies conducted to measure the effectiveness of online courses focused on factors such as number of hits, time on task, and overall student participation measured by a LMS (Davies & Graff, 2005; Ryabov, 2012). The results of these studies were limited in scope because the data only accounted for a portion of the student overall course activities.

Other studies focused only on the mode of delivery and found little difference between delivery modes (Dell, Lowe, & Wilker, 2010; Kury et al., 2007). These studies typically included relatively small numbers of students enrolled over the course of just one or two semesters. An exception was a longitudinal study conducted by Wagner, Garippo, and Lovaas (2011) where data was collected on 624 students over the course of 9 academic years. However, they "found no significant difference between the two modes of course delivery" (Wagner et al., 2011, p. 68).

Some studies included the impact of demographics on student learning such as age, gender, previous academic performance as measured by grade point average (GPA), and academic level (Kury et al., 2007; Ryabov, 2012). Viewed jointly, these studies found inconsistencies regarding the effects on learning based on these demographics. However, Ryabov found that strong previous academic achievement "increased the odds" (p. 21) of student success.

Additional studies comparing course delivery mode, such as the one conducted by Dell, Low, and Wilker (2011), randomized the student work to be studied; that is, the graders did not know which mode the students were in. In other studies, the delivery mode was clearly known, and the same instructor taught all modes and graded all assessments (Ashby, Sadera, & McNairy, 2011; Ryabov, 2012; Wagner et al., 2011). These studies eliminated the problem frequently associated with studies that compare different modes: multiple instructors (Ashby et al., 2011).

This study was unique in scope because it included analysis of data from two separate courses, and also included an analysis of the effect of delivery mode on student performance from one course to the next downstream course; the first course was delivered in three different modes and the downstream course was conducted in two. Data was collected from both courses over four semesters. The results of this study using multiple sections of the same course taught by the same instructor over a 2-year period of time, and comparing course performance in a downstream course offered in F2F and online modes, may contribute to the overall literature on student performance in F2F, online, and hybrid courses.

Method

Background

The purpose of this research was to determine if there was a significant difference in student success in an introductory information systems course based on three different modes of delivery: F2F, online, and hybrid. As this study progressed, additional data was made available by the institution regarding student performance as measured by final grades in a subsequent information systems course for which the introductory class was a prerequisite. The researchers used final grades as a measure of learning outcomes in each course, similar to other studies comparing different modes of delivery (Ashby, et al, 2011; Dzuiban, Hartman, & Moskal, 2004). Sufficient data was provided to analyze business majors' performance in the downstream course based on: (1) whether they took that course F2F or online; (2) whether they took the introductory course in F2F, online, or hybrid delivery modes; and (3) their learning success in the original course.

As the world of online learning is developing, so is the terminology that is used to describe it. For this study, *F2F delivery mode* was used to describe the course sections that were taught where students attended a classroom on the physical campus and the instructor was present. *Online delivery mode* was defined as any course that delivered all course material via the Internet with no required F2F meetings between student and instructor.

The last iteration of delivery mode of the course was referred to as hybrid. Blended or hybrid appear frequently in the literature to describe everything from courses converting one F2F class meeting per week to an online activity, to courses that only meet F2F twice during the semester (Brunner, 2006; Picciano, 2006; Toth, Amrein-Beardsley, & Foulger, 2010; Twigg, 1999; The Sloan Consortium, 2005). For the purposes of this study the term *hybrid*, as defined by Kaleta, Garnham, and Aycock, (2005) was used to describe "courses in which a significant portion of the learning activities have been moved online, and time traditionally spent in the classroom is reduced but not eliminated" (p. 1).

The online version of IS100 was developed and implemented in Fall 2010 and was offered simultaneously for four consecutive semesters by the author-instructor along with the F2F version. In each semester, students self-selected the delivery mode based on the descriptions of the classes in the course schedule. The F2F sections of IS100 met twice weekly and exams were held during the regular class meetings. There were several independent workdays offered during the semester before final project due dates so that students could receive hands-on assistance from the instructor.

In the online section of IS100 there were no F2F meetings, but the instructor was available during office hours, and students could take advantage of the independent workdays that were scheduled for the F2F sections. The hybrid course was first offered in Fall 2011 and again in Spring 2012. There were 10 F2F meetings of IS100 scheduled each semester, and every week optional support labs were offered and staffed by the instructor, graduate assistants, and peer tutors. During weeks without F2F meetings, students were responsible for independent work supported by instructor-developed resources available to all students in all sections.

All IS100 students enrolled in any of the three modes of delivery had web access to the recorded lectures, which could be viewed multiple times. All exam reviews were also recorded and available to all students. Ensuring all students had access to, and were responsible for, the same assignments reduced the possibility of course drift.

Exams for all course delivery modes in IS100 were available in the LMS, and results recorded in the LMS grade book. There were four exams, and all but one were in a multiple choice format. For F2F and hybrid sections of IS100, exams were held during regular class meetings and were proctored by the instructor. Students in online mode were allotted the same amount of time, but were not proctored by the instructor.

Student data acquired from the University's Office of Research such as GPA, demographics, and delivery mode were made available to the authors for analysis related to the performance of the IS100 students in the second course, IS200. Since this course did not fulfill any general education requirements, it was assumed that all students enrolled in IS200 were business majors (data regarding students' declared majors was not available to the authors). During the two-year time frame of this study, 217 students that completed an IS100 section offered by the author-instructor later enrolled in IS200. Of those students, 62 enrolled in an online section, and 155 enrolled in a F2F section of IS200.

Analytic Approach

Differential student success, as measured by grades earned in IS100 in each of the three different delivery modes of IS100, was examined. Then, the effect that IS100 academic achievement and delivery mode had on a student's performance in the downstream IS200 course was examined. Additionally, several other potential learning determinants identified in the literature (Kury, Jones, Arney, & Lovett, 2007; Ryabov, 2012) were evaluated for their significance in this exploratory statistical analysis.

A series of three ordered probit regression models were estimated to relate student performance in IS100 and IS200 to sets of possible explanatory variables. The first model was developed to determine the significance of each of the potential explanatory variables in a model predicting students' performance in IS100. Based upon the results of the estimation of the initial model, a second, more parsimonious, ordered probit model was then developed and estimated to predict students' performance in IS100. Finally, a third ordered probit model was developed and estimated to predict IS200 student performance utilizing similar variables employed in the parsimonious IS100 learning model along with the inclusion of two additional categorical variables that indicate: (1) the IS100 delivery mode; and (2) the learning outcome in IS100 (letter grade) for each student in the original sample that later completed IS200. This final ordered probit regression model was developed to determine if IS100 delivery modes and learning outcomes were statistically significant predicators of student performance in IS200, while controlling for other relevant individual student attributes.

Ordered probit regression is an appropriate modeling methodology as it embodies the assumption that there exists an unobservable continuous latent variable (student learning in this case) that, along with a random factor, determines an observable categorical dependent variable (the course letter grade in this case) possessing a natural rank order (Becker & Kennedy, 1992; Greene, 2000). The A to F grading scheme is a natural ordered categorical scale where the difference between letter grades is not directly quantifiable. Maximum likelihood estimation procedures are used to fit the models, similar to a recent study that employed a maximum likelihood estimation of a multinomial logistic model to examine the effect of time spent online with course content on student grades (Ryabov, 2012). The Ryabov model was extended by the authors in this case to incorporate the additional information embodied by the natural ordering associated with letter grades as letter grades earned are naturally ordered categorical outcomes.

Data

Many possible determinants of academic performance such as age, gender, prior academic experience, and prior academic success have been identified in the literature (Kury et al., 2007; Ryabov, 2012). From the researcher's institution, student demographical information regarding age, gender, Pell Grant eligibility (as a measure of the external availability of resources), area of residence (as a measure of proximity to campus), and academic level (measured by academic class level) were gathered and controlled for in this study. Prior student GPA, or prior academic achievement had been shown to impact learning outcomes (Kury et al., 2007; Ryabov, 2012), and is therefore included as a possible explanatory variable as well.

Information concerning these variables for every student enrolled in the F2F, online or hybrid sections of IS100 taught by the author-instructor from the Fall 2010 through Fall 2012 semesters was acquired from the researcher's institution for this analysis yielding a total of 382 student observations. Of 382 students, 233 had prior academic achievement at the research institution as measured by the presence of a cumulative institutional GPA at the conclusion of the semester prior to the student enrolling in IS100. Focus was placed on creating ordered probit models for these 233 students, as student GPA is a powerful predictor of student success (Bernard, Brauer, Abrami, & Surkes, 2004; Bethune, 2010; Li, Uvah, & Amin, 2012; Ryabov, 2012). Of the 233 students with prior academic achievement that earned a letter grade in IS100, 130 students subsequently enrolled in and completed IS200.

Table 1 presents the distribution of letter grades earned by delivery mode for all 382 students enrolled in the author-instructor's sections of IS100 from Fall 2010 through Fall 2012. Table 1 shows that the distribution of letter grades is not uniform across delivery modes. It also highlights the relatively small number of students receiving D or F letter grades in all delivery modes.

Table 1. *Cross tabulation of IS100 letter grade by delivery mode*

IS100 Letter Grade	IS100 Delivery Mode			Total
	F2F	Online	Hybrid	
A	54	62	25	141
B	34	44	52	130
C	14	25	27	66
D	1	4	13	18
F	6	9	12	27
Total	109	144	129	382

For the purposes of the ordered probit models, letter grades earned in IS100 or IS200 were grouped into three distinct ordered categories for each class; exceptional learning (the student exceeded instructor expectations and earned an A), acceptable learning (the student met instructor expectations and earned a B in the class), and less than acceptable (the student failed to meet instructor expectations and earned a C or lower in the class). This ordered grouping facilitated the use of meaningful Chi-Square tests in distribution comparisons across delivery modes. The conditional difference in the distribution of learning outcomes in IS100 (exceptional, acceptable, and less than acceptable) across delivery modes (F2F, online, and hybrid delivery) was evaluated using a Pearson Chi-Square test with the authors finding that there was no supported significant difference in the distribution of learning outcomes across delivery modes at the 0.000 significance level. Clearly, observed learning outcomes in IS100 are different across delivery modes with students enrolled in hybrid and online sections exhibiting less frequent exceptional learning outcomes and more frequent less than acceptable learning outcomes relative to those enrolled in a F2F delivery section as seen in Table 1.

It was noted that students self-select delivery mode in the sample and, therefore, the authors investigated the possible impacts of self-selection on learning. Table 2 presents a brief summary of that investigation.

Table 2. *Selected Descriptive Statistics*

IS100 Delivery Mode	Age (yrs)	Pre-IS100 GPA (4.0 max)	Percent Female	Percent Pell Qualified	Percent with a Pre-IS100 GPA

F2F	Mean	21.64	2.9774	51%	37%	63%
	N	109	69			
Online	Mean	24.85	2.8623	56%	51%	78%
	N	144	112			
Hybrid	Mean	23.00	2.5290	41%	47%	40%
	N	129	52			
Total	Mean	23.31	2.8220	49%	46%	61%
	N	382	233			

The data revealed, first, that students self-selecting the F2F and online delivery mode with prior academic achievement at the institution had greater prior academic achievements (as measured by higher pre-IS100 GPAs) than students self-selecting the hybrid delivery mode and, second, that students self-selecting the F2F delivery mode were younger than those opting for online or hybrid delivery. Both the difference in mean age and mean level of prior academic achievements were significantly different by delivery mode at levels less than 0.003 in ANOVA tests. Further, it was noted that there were also significant differences in self-selection to delivery mode by female students relative to male students (males were more likely to enroll in hybrid IS100 sections than females), by county of residence (students with nearby residences were more likely to enroll in F2F IS100 sections), by Pell Grant eligibility (Pell Grant-eligible students were more likely to enroll in online or hybrid IS100 sections), and by students with prior evidence of academic achievement as evidenced by a pre-IS100 GPA (students with a pre-IS100 GPA were less likely to enroll in the hybrid sections). These self-selection effects exhibited by students could have differential impacts on the observed distributions of learning outcomes.

Ordered Probit Models

To control for possible self-selection effects in observed learning outcomes, a set of three ordered probit regression models was employed to derive the estimated likelihood of attaining a specific observable achievement level in a class conditional on class delivery mode and the observed demographic and prior academic achievement variables of each student. In these analyses, observable student performance in a class was categorized into three ordered outcomes. These outcomes were labeled exceptional (Y = 2), acceptable (Y = 1), and less than acceptable (Y = 0). Model 1 below presents the full IS100 ordered probit model, which includes all theorized possible explanatory variables for which the institution provided data.

Model 1: Ordered Probit Model for Learning Outcomes in IS100

In Model 1, the entire set of available categorical demographical variables was employed as performance predictors. Additionally, the continuous variable student cumulative GPA prior to enrolling in IS100 (PreIS100GPA) and the categorical variable of delivery mode of IS100 were also used. Table 3 presents the definitions of the explanatory variables employed in this ordered probit model of student learning outcomes in IS100.

Table 3. *Model Variables: Ordered Probit Model for Learning in IS100*

Coefficient	Descriptive	Variable Type
β_0	Intercept	-
β_1	Age of student	Continuous
β_2	Cumulative GPA	Continuous
β_3	Pell Eligibility	Binary

β_4	Female	Binary
β_5	Area 1	Binary
β_6	Area 2	Binary
β_7	Area 3	Binary
β_8	Area 4	Binary
β_9	Freshman	Binary
β_{10}	Sophomore	Binary
β_{11}	Junior	Binary
β_{12}	IS100 F2F Delivery Mode	Binary
β_{13}	IS100 Online Delivery Mode	Binary

Formally, Model 1 is:

$$y^* = \beta_0 + \beta_1 * Age + \beta_2 * PreIS100GPA + \beta_3 * PellEligble + \beta_4 * Female + \beta_5 * Area1 + \beta_6 * Area2 + \beta_7 * Area3 + \beta_8 * Area4 + \beta_9 * Freshman + \beta_{10} * Sophomore + \beta_{11} * Junior + \beta_{12} * IS100Facetoface + \beta_{13} * IS100Online + \epsilon$$

where y^* represents the unobservable latent variable of student learning in IS100 and

$Y = 0 \; if \; y^* \leq \delta_0$

$Y = 1 \; if \; \delta_0 < y^* \leq \delta_1$

$Y = 2 \; if \; y^* > \delta_2$

$\epsilon \sim n(0, \sigma^2)$

The threshold values, δ_0, δ_1, and δ_2, respectively, are used to categorize y^* into either the less than acceptable category ($Y = 0$), the acceptable category ($Y = 1$), or the exceptional category ($Y = 2$). The likelihood of a student achieving a less than acceptable learning outcome is then given by $\Pr(y^* \leq \delta_0)$, an acceptable learning outcome by $\Pr(\delta_0 > y^* \leq \delta_1)$, and an exceptional learning outcome by $\Pr(y^* > \delta_2)$. To identify Model 1 for maximum likelihood estimation it was assumed that δ_0=0 and σ^2=1 and that the omitted base case of the ordered probit regression model was the learning outcome of a male student that was not Pell eligible, resided in area 5, was a senior, and was enrolled in the hybrid course.

To summarize, Model 1 controlled for five categorical variables modeled as sets of binary variables (gender, area of residence, Pell Grant qualified, academic class level, and course delivery mode) and two continuous variables (age and cumulative GPA). The parameter estimates, standard errors, and significance levels for each variable in Model 1 are presented and discussed in the Results section below.

Model 2: Parsimonious Ordered Probit Model for Learning Outcomes in IS100

Model 2 was developed and estimated to test the hypothesis that a subset of the predictor variables employed in Model 1 had no significant effect on predicting student learning in IS100. This test might yield a more parsimonious model to predict observable learning. Specifically, the following hypothesis was employed in constructing the potentially more parsimonious model:

$H_0: \beta_1 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{13} = 0$

The specific form of this model is:

$$y^* = \beta_0 + \beta_2 * PreIS100GPA + \beta_{12} * IS100Facetoface + \epsilon$$

where

y^* represents the unobservable latent variable of student learning in IS100

and

$Y = 0 \; if \; y^* \leq \delta_0$

$Y = 1 \; if \; \delta_0 < y^* \leq \delta_1$

$Y = 2 \; if \; y^* > \delta_2$

$$\epsilon \sim n(0, \sigma^2)$$

To identify this model for estimation, δ_0=0 and σ^2=1 were again assumed. The parameter estimates, standard errors and significance levels for each variable in Model 2 are presented and discussed in the Results section below.

Model 3: Parsimonious Ordered Probit Model for Learning Outcomes in IS200

Model 3 was developed as a parsimonious model to predict learning outcomes in IS200. The form of this model was based on the form of Model 2 described above with the inclusion of three additional binary indicator variables to identify for each student: (1) if IS100 was completed in F2F delivery mode; (2) an exceptional learning outcome was achieved in IS100; or (3) an acceptable learning outcome was achieved in IS100. Table 4 presents the definitions of the explanatory variables employed in this ordered probit model of student learning outcomes in IS200.

Table 4. *Model Variables: Ordered Probit Model for Learning in IS100*

Coefficient	Descriptive	Variable Type
β_{14}	Intercept	---
β_{15}	Pre IS200 GPA	Continuous
β_{16}	IS200 F2F Delivery Mode	Continuous
β_{17}	Exceptional IS100 Learning	Binary
β_{18}	Acceptable IS100 Learning	Binary
β_{19}	IS100 F2F Delivery Mode	Binary

β

Formally, Model 3 is given by:

$$y^* = \beta_{14} + \beta_{15} * PreIS200GPA + \beta_{16} * IS200Facetoface + \beta_{17} * IS100Exceptional\ Outcome + \beta_{18} * IS100Acceptable\ Outcome + \beta_{19} * IS100Facetoface + \epsilon$$

where

y^* represents the unobservable latent variable of student learning in IS200

and

$Y = 0 \; if \; y^* \leq \delta_0$

$Y = 1 \; if \; \delta_0 < y^* \leq \delta_1$

$Y = 2 \; if \; y^* > \delta_2$

$$\epsilon \sim n(0, \sigma^2)$$

To identify Model 3 for maximum likelihood estimation it was assumed that δ_0=0 and σ^2=1 and that the omitted base case of the ordered probit regression model was the learning outcome in IS200 of a student that had a less than acceptable learning outcome in IS100 and had not taken IS100 in the F2F delivery mode. The parameter estimates, standard errors, and significance levels for each variable in Model 3 are presented and discussed in the Results section below.

Results

Model 1: Ordered Probit Model for Learning Outcomes in IS100

The results of the estimation of Model 1 (N = 233) are presented in Table 5. Table 5 indicates that the estimated model did a significantly better job of predicting students learning outcomes in IS100 than a model that predicted student learning outcomes without the effects of any explanatory variables (the Intercept-Only Model) as evidenced by the highly significant change in -2 Log Likelihood values associated with the final model. Further, Table 5 suggest that the threshold estimates, the explanatory variable of pre- IS100 GPA and the explanatory variable of student selection of the F2F mode of IS100 delivery were highly significant predictors of improved observable learning outcomes with higher GPAs associated with increased likelihoods of better learning outcomes in IS100, and students taking the F2F delivery mode of IS100 also associated with increased likelihoods of better learning outcomes.

Table 5. *Estimation results for Model 1: Ordered Probit Model for Learning in IS100*

Variable	Parameter Estimate	Std. Error	Wald Stat	df	Sig.
Threshold Y=2	3.633	.655	30.732	1	.000
Threshold Y=1	2.508	.638	15.447	1	.000
AGE	.017	.014	1.502	1	.220
Pre-IS100 GPA	.856	.126	46.221	1	.000
Female	-.143	.163	.772	1	.380
Area1	.127	.409	.096	1	.757
Area2	.280	.353	.629	1	.428
Area3	.643	.486	1.750	1	.186
Area4	.335	.384	.762	1	.383
Pell Qualified	.136	.169	.646	1	.422
Freshman	.003	.267	.000	1	.990
Sophomore	.189	.267	.502	1	.479
Junior	.080	.208	.150	1	.699
F2F Delivery	.662	.235	7.915	1	.005
Online Delivery	.086	.204	.176	1	.674

Model Fitting Information

Model	-2 Log Likelihood[a]	Chi-Square	df	Sig.
Intercept Only	493.607			
Final	412.016	81.591	13	.000

a. The kernel of the log-likelihood function is displayed.

Model 2: Ordered Probit Model for Learning Outcomes in IS100

Based on the results of the estimation of Model 1 that indicated many potential predictors of student learning outcomes were individually insignificant predictors of learning outcomes, Model 2 was estimated to test the hypothesis that a subset of the predictor variables jointly had no significant effect on predicting student learning in IS100. This might yield a more parsimonious model to predict observable learning outcomes. Specifically, the following hypothesis was employed in constructing Model 2:

$$H_0: \beta_1 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{13} = 0$$

Table 6. *Estimation results for Model 2: Ordered Probit Model for Learning in IS100*

Variable	Parameter Estimate	Std. Error	Wald Stat	df	Sig.
Threshold Y=2	2.228	.373	35.607	1	.000
Threshold Y=1	1.128	.357	9.986	1	.002
Pre-IS100 GPA	.876	.117	55.747	1	.000
F2F Delivery	.651	.178	13.311	1	.000

Model Fitting Information

Model	-2 Log Likelihood[a]	Chi-Square	df	Sig.
Intercept Only	498.177			
Final	420.763	77.414	2	.000

a. The kernel of the log-likelihood function is displayed.

Table 6 indicates that, similar to Model 1, Model 2 did a significantly better job of predicting student learning outcomes in IS100 than a model that predicted student learning outcomes without the effects of two explanatory variables (the Intercept-Only Model), as evidenced by the highly significant change in -2 Log Likelihood values associated with the final model. Further, the parameter estimates associated with the pre-IS100 GPA, and the F2F mode of delivery of IS100, are similar to the estimates of those coefficients derived from Model 1.

Further, H_0 was tested by comparing the difference between the -2 Log Likelihood values of Model 1 and Model 2, which under the assumption that H_0 was true, was distributed as a Chi-Square random variable with 11 (13 - 2) degrees of freedom. The difference in the -2 Log Likelihood values between Model 1 and Model 2 is equal to 8.747, which has an associated probability value of 0.6452; therefore, H_0 was not rejected. Model 2 is indeed a more parsimonious model to predict student learning outcomes in IS100.

Model 3: Parsimonious Ordered Probit Model for Learning Outcomes in IS200

Based upon the results obtained in estimating Model 2, Model 3 was developed as a parsimonious model to predict learning outcomes in IS200. The form of this model was based on the form of Model 2 above with the inclusion of a binary variable to indicate if the student taking IS200 took IS100 in the F2F delivery mode and two explanatory binary indicator variables to categorize the learning outcome of the student in IS100 (exceptional or acceptable). The other variables used as explanatory variables in the IS200 learning in Model 3 were cumulative student GPA prior to IS200 as a measure of prior student performance and IS200 delivery mode. The results of the estimation of Model 3 are presented in Table 7 (N=130).

Table 7 indicates that the estimated model did a significantly better job of predicting student learning outcomes in IS200 than a model that predicted student learning outcomes without the effects of any of the explanatory variables (the Intercept-Only Model), as evidenced by the highly significant change in -2 Log Likelihood values associated with the final model.

Table 7. *Estimation results for Model 3: Ordered Probit Model for Learning in IS200*Variable	Parameter Estimate	Std. Error	Wald Stat	df	Sig.
Threshold Y=2	3.438	.515	44.579	1	.000
Threshold Y=1	2.071	.483	18.423	1	.000
Pre-IS200 GPA	.869	.168	26.679	1	.000
IS200 F2F	-.175	.208	.708	1	.400
IS100 Online or Hybrid	.570	.200	8.143	1	.004
Exceptional IS100 Learning	.982	.292	11.353	1	.001
Acceptable IS100 Learning	.011	.247	.002	1	.965

Model Fitting Information

Model	-2 Log Likelihood[a]	Chi-Square	df	Sig.
Intercept Only	430.806			
Final	319.552	111.254	5	.000

a. The kernel of the log-likelihood function is displayed.

The results displayed in Table 7 indicate that delivery mode of IS200 was not a significant predictor of student performance in IS200, unlike the results from models 1 and 2 that showed that delivery mode is significant in IS100. However, similar to the learning models for IS100, student GPA was a highly significant predictor of student learning in IS200. Students that had exceptional learning outcomes in IS100 were also more likely to have better learning outcomes in IS200.

The most interesting result in the estimation of this model is that students who took the IS100 class online or in hybrid delivery mode outperformed those students in IS200 who took the F2F version of IS100. Recall that the students taking the F2F version of IS100 outperformed students in the online and hybrid versions of IS100.

Finally, the diagnostic Brant (1990) test of parallel lines was passed by all three models, ensuring that the slope coefficients (parameter estimates) were the same across all response categories.

Discussion

The findings of this study suggest that demographics such as age, gender, area of residence, Pell Grant qualified, and academic class level are not statistically significant factors in student success in an introductory information systems course despite the mode of course delivery. The results of this study did indicate that students self-selecting the F2F and online delivery modes had higher GPAs than students self-selecting the hybrid delivery mode. The only self-selection effect found to be significant for better learning outcomes was selection of the F2F mode of the course, along with the pre-IS100 GPA.

In this study, a student's GPA was found to be a highly significant factor in a student's success in the introductory information systems course, whether it was taken in F2F, online, or hybrid mode. One possible explanation for this is that students who have developed study habits that lend themselves to a particular level of success continue to demonstrate that level regardless of course delivery method. This study also found that the most significant factor in determining student success in the second more advanced information systems course was also the student's GPA. These findings may contribute to the literature that GPA is the most significant factor in determining student success in any mode of course delivery (Bernard, Brauer, Abrami, & Surkes, 2004; Bethune, 2010; Li, Uvah, & Amin, 2012).

This study also found that students who took IS100 in the F2F version had statistically better learning outcomes than students in the other two delivery formats. These findings could be explained in a number of ways. One may be that the instructor was available for one-on-one assistance during every class meeting, so students may have been more in tune with what the instructor was looking for in assessments. Or, since IS100 has qualitative components, the instructor's more personal interaction with those students in the F2F sections may have impacted the grading of assessments.

The most compelling finding in this study was that students who had taken IS100 in online or hybrid mode delivery did significantly better, as a group, in the second more advanced information systems course than those students who had taken IS100 in the F2F mode. There may be multiple reasons for this finding. However, one explanation could be based on constructivist theories of learning that argue that students who are actively involved in the learning process are more successful and retain more (Grabe & Grabe, 2007). Studies have found that in online and hybrid environments, instructors are more likely to act as facilitators, allowing students to become more active participants in the learning process (Dziuban, 2004; Vernadakis, Antoniou, Giannousi, Zetou, & Kioumourtzog, 2011).

The results of this study could be important to online instructors and program administrators because, according to this study, online and hybrid instruction had positive results in student learning in the next downstream course. Further studies would be beneficial to the literature comparing online, hybrid, and F2F delivery modes to student performance in more advanced level courses.

Conclusion

Based on the findings of this research the most consistent determiner for student success, regardless of delivery mode in two consecutive information systems courses was prior cumulative GPA. This study also found that students who took the initial information systems course in the F2F mode of delivery did have a significantly better chance for academic success as opposed to those who took it in the online or hybrid modes of delivery. However, the most remarkable finding of this study was that those students who took the initial course in online or hybrid delivery mode showed greater success, as a group, in the second, more advanced information systems course, as measured by course grade, than students who took the initial information systems course in the F2F mode.

This study is unique in the literature because it first provided an analysis of student performance in a course, with three separate modes of delivery and one instructor, and then provided an analysis of student performance in a subsequent higher level course based on delivery mode in the original introductory course. Although this study finds that the mode of delivery of the introductory information systems course does have a statistically significant impact on student performance in the subsequent information systems course, generalizations cannot be made to other courses or even to the same course taught by different instructors. Since the courses that were examined in this study have qualitative components, conducting a similar study analyzing a quantitative course may add to the body of knowledge on student performance via different modes of course delivery. Similar longitudinal studies would add to the literature comparing student performance in consecutive courses.

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