Using Course-Level Factors as Predictors of Online Course Outcomes: A Multilevel Analysis at a U.S. Urban Community College

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ABSTRACT

Research has documented lower retention rates in online versus face-to-face courses. However, little research has focused on the impact of course-level characteristics (e.g. elective vs. distributional vs. major requirements; difficulty level; STEM status) on online course outcomes. Yet, focusing interventions at the course level versus the student level may be a more economical approach to reducing online attrition.

This study used multi-level modeling, and controlled for the effects of both instructor-level and student characteristics, to measure the relationship of course-level characteristics with successful completion of online and face-to-face courses. Elective courses, and to a lesser extent distributional course requirements, were significantly more likely to have a larger gap in successful course completion rates online versus face-to-face, when compared with major course requirements. Upper level courses had better course completion rates overall, but a larger gap in online versus face-to-face course outcomes than lower level courses.

KEYWORDS: Online learning; Course type; Retention

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INTRODUCTION

The landscape of higher education in the past decade has undergone a virtual transformation-- with the proliferation of online course offerings being used to augment enrollment and changing life style needs. Enrollment in online learning is far exceeding the growth of higher education generally; particularly for community colleges, who have almost universally embraced online learning as a way to better serve their large number of non-traditional students (Allen and Seaman 2010; 2013; CCRC 2013; Parsad, Lewis and Tice 2008). Attendant with the rise of online learning is the on-going concern that attrition rates in online courses are significantly greater than those found for face-to-face courses (Boston and Ice 2011; Hachey, Wladis & Conway 2013, 2014; Howell, Williams and Lindsay 2003). However, despite the rapid growth of online learning and the related concern on online attrition, a clear understanding of the factors affecting course outcomes, especially at the community college level is lacking (CCRC 2013; Hachey, Wladis & Conway 2012; 2013; Wladis, Conway & Hachey, 2015).

The majority of the research has investigated online student characteristics (Layne, Boston and Ice 2013; for reviews, see Levy 2007 and Yukselturk and Bulut 2007; Wladis, Hachey & Conway, 2014a; Wladis, Conway & Hachey, 2015). However, very little research has examined course-level factors as predictors, even though they have been posited as having a potential impact on course outcomes (Diaz 2002; Wladis, Hachey & Conway, 2014b, 2014c). To address this gap, this study explores the extent to which course-level factors (elective vs. distributional vs. major requirement; difficulty level; STEM vs. non-STEM) may be used to predict online versus face-to-face course outcomes while controlling for other potentially mediating student characteristics that are often mentioned in the online literature (academic preparation, gender, ethnicity, age, financial aid/SES and ESL/citizenship status). We contend that examining the effect of course-level factors on predicting online outcomes may be critical to ameliorating the online attrition problem; rather than focusing on individual online students who have a varied list of at-risk characteristics, it may be more practical for institutions to target support services at specific courses.

LITERATURE REVIEW

Online learning in higher education

Online learning is often viewed as a valuable way of providing universal education and as such, online courses are now a core instructional medium at most colleges and universities in the U.S. (Caswell, Henson Jensen and Wiley 2008; Sutton and Nora 2008). Over a decade of studies and meta-analyses have shown no clear positive or negative effect of learning outcomes online versus face-to-face, as assessed by exams or course grades (Bowen and Lack 2012; Jaggers 2011; U.S. Department of Education 2011). In particular, Bernard et al.'s (2004) large-scale meta-analysis of the online learning literature avers that online courses provide students with access without compromising the quality of instruction. The trend toward online learning is expected to continue: over two-thirds of chief academic officers assert that online learning is a critical part of their institution's long term strategy (Allen and Seaman 2013; CCRC 2013).

The prevalence and continued expected growth of online learning is particularly visible at community colleges, where online learning has become a central way of meeting enrollment demands (CCRC 2013). Over 97% of community colleges have online course offerings, community colleges have the highest enrollment rates of all higher education institutions offering online courses, and almost half of all E-learning programs in the U.S. are hosted by community colleges (Obama 2012; Parsad, Lewis and Tice 2008). Moreover, since 2010, online enrollments at the community college level have risen over 29% (CCRC 2013). Currently, more than 60% of all community college students take at least one course during their academic career and this trend toward online course taking is expected to increase (CCRC 2013; Pearson Foundation 2011).

However, the value of online learning, both to institutions and students alike, has been called into question because of attrition rates that are 7-20 percentage points higher in online courses versus face-to-face courses, and overall online attrition rates of 30-40% (Boston and Ice 2011, Hachey, Wladis & Conway, 2013a; Morris and Finnegan 2008-9; Patterson and McFadden 2009). Although online courses may provide critical access to community college students (Allen and Seaman 2010; Cox 2005; Jaggers and Xu 2010), the high attrition rates associated with online courses have also been connected to academic non-success and may hinder academic momentum, which is critical in overall college persistence (Attewell, Heil, and Reisel 2011; CCRC 2013; Diaz 2002). Overall, little is known about factors impacting online attrition and the effectiveness of online courses for community college students (CCRC 2013).

Course-level factors which may influence online retention

Student reason/motivation for taking a course (elective, distributional or major requirement)

In a previous study (Wladis, Hachey & Conway, 2014b), we found that community college students who took an online course that fulfilled their major requirements were equally likely to remain in the course whether they took it online or face-to-face. However, students who took an online elective or a distributional requirement were much more likely to withdraw than in the face-to-face environment, with this difference being particularly pronounced for elective courses. These findings mirror Reed (1981) in the traditional higher education literature, who found greater drop-out for face-to-face elective courses, with course persistence significantly related to a students' belief in the relevance of the course to their academic need. To our knowledge, our previous study is the first that looks at whether the enrollment decision in required versus elective online courses has an impact on online retention. We found that motivation for enrolling in the online environment can impact course outcomes; however, additional empirical analysis on other samples controlling for student characteristics and random instructor-level effects is needed to substantiate these findings.

Course difficulty level

In this paper, course difficulty is defined using a course's enrollment prerequisites. In this study, lower level (100-level) courses have no credit-bearing prerequisites; in contrast, upper level (200-level and above), cover more advanced material and require at least one 100-level course as a prerequisite. There are, of course, other ways in which the difficulty level of a course could be interpreted, but we do not purport to cover all of those interpretations here; our goal is simply to distinguish between courses which have credit-bearing pre-requisites versus those that do not. This particular distinction is based on research showing that students in lower-level courses may be more vulnerable to doing worse online than would be expected given their face-to-face performance.

Difficulty of instructional materials has long been posited as a potential reason for drop-out in online courses (Diaz 2002). Prior research has indicated a strong negative correlation between attrition and previous education in the field; this suggests that students may be more likely to drop out of lower level online courses, particularly if courses outside their major (Xenos, Pierrakeas and Pintelas 2002). In a prior study (Wladis, Hachey & Conway, 2014b), we found that lower level courses taken as either electives or to fulfill distributional requirements had highly statistically significantly (α=0.01) lower retention rates online than face-to-face, whereas this effect was not seen for major requirements or for upper level community college courses. Our previous finding substantiates other recent work that found that students enrolled in lower level classes (which are typically taken earlier in a college career) have a greater risk of course drop-out; Jaggers and Xu (2010) and Xu and Jaggers (2011) found that community college students who took online classes early in their college careers had higher attrition than those who took only face-to-face courses. Although still tentative, the evidence is indicating that course difficulty level may be a factor in online attrition.

STEM versus non-STEM courses

Little research has been conducted to determine if the online environment affects course outcomes for STEM and non-STEM courses differently. The studies which have been conducted on online STEM courses have often focused on a single course and/or have not conducted comparative analysis between STEM and non-STEM courses, and suggested either no impact (Kartha 2006; McLaren 2004) or some modest positive impact (Reuter 2009) of the online environment on STEM course outcomes. In a recent larger scale study (analyzing 122 community college course sections), we found that attrition rates in STEM courses were more strongly increased by the online environment than in non-STEM courses. In particular, the course types with significantly higher attrition online were lower level STEM courses taken as electives or distributional requirements (Wladis, Hachey & Conway, 2014c), suggesting that whether a course is in a STEM subject or not may influence how the online environment impacts course outcomes.

Student-level factors which may influence online retention

Academic Preparation

Academic preparation (specifically G.P.A.) has been posited as a mediating variable affecting online course outcomes; higher levels of academic preparation have been correlated with higher rates of completion and success in traditional face-to-face courses (Allen, Robbins, Casillas and Oh 2008; NCES 2005). Several studies have found students who elect to enroll in online courses are more likely to have higher levels of academic preparation (Jaggers and Xu 2010; Xu and Jaggers 2011), whereas others have not found a significant relationship between G.P.A. and online enrollment (Hachey, Wladis & Conway, 2012, 2014; Wladis, Hachey & Conway, 2014a). Further research has suggested that G.P.A. may be positively correlated to online course outcomes, although it is not clear the extent to which this relationship is any more significant than it is in face-to-face courses (Aragon and Johnson 2008; Morris, Wu and Finnegan 2005; Hachey, Wladis & Conway, 2013; for a review, see Xu and Jaggers 2013).

Demographic Characteristics

A variety of student demographic characteristics have been explored in the online learning literature. Although much of the research on demographic variables is conflicting (Jones 2010), several key characteristics have been repeatedly posited as having an effect on online enrollment and course outcomes. For this study, we have chosen to include demographic characteristics which either seem to have the best evidence as having a potential impact on online course outcomes or have been repeatedly mentioned in the literature but not rigorously tested.

In particular, gender, ethnicity and age have been named in the online research as potential important factors. Older (24 years and above) students make up almost half of higher education enrollments and females make up well more than half of the higher education population (Howell, Williams and Lindsay 2003). Profiles of online learners mirror this, with the research showing online learners are more likely be older and female (Aslanian and Clinefelter 2012; Noel-Levitz 2011; Moore and Kearsley 2005). Both of these characteristics are correlated with higher rates of persistence and success in higher education generally, suggesting they are a mediating factor (Bean and Metzner 1985; Chee 2005; Freeman 2004; Halsne and Gatta 2002; Jaggers and Xu 2010; Moore and Kearsley 2005; Qureshi, Morton and Antosz 2002; Xu and Jaggers 2011). However, although the research does show that age and gender effect online enrollment (, Wladis, Conway & Hachey, 2015; Wladis, Hachey & Conway, 2014a), less is known about the effect of age and gender on online course outcomes. Some research suggests that gender has no impact on outcomes (Astleitner and Steinberg 2005; Lu, Yu, and Liu 2003; Yukselturk and Bulut 2007), while other studies point to better success for female students (Chyung 2007; Price 2006; Xu and Jaggers 2011). Several studies support the idea that older students perform better than younger students online (Colorado and Eberle 2010; Xu and Jaggers 2011; Wladis, Conway & Hachey, 2015). Further, although a few studies have shown ethnicity to be non-significant (Aragon and Johnson 2008; Welsh 2007), there is a growing body of evidence that suggests that minorities are less likely to enroll and may be more likely to have worse outcomes in comparison to White students in the online environment, particularly at community colleges (Angiello 2002; Conway, Wladis & Hachey, 2011; Xu and Jaggers 2013, Wladis, Hachey & Conway, 2014a). These findings suggest that further investigation is needed as to the effects of gender, ethnicity and age on online course outcomes.

Two other factors, English as a Second Language (ESL)/Immigrant status and Socio Economic Status (SES), have been repeatedly suggested in the research as potentially impacting online outcomes, yet little rigorous research has focused on these factors among online community college students. ESL and immigrant status have been posited as having a negative effect on online outcomes (Lopez, Gonzalez-Barrera, and Patten 2013; The New American Consumer 2012; 2014c), since ESL students have been shown to lag behind the national average in personal computer ownership/Internet usage and to possess fewer technical skills (File 2013; Rainie 2010). Additionally, recent research (Jaggers and Xu 2010; Xu and Jaggers 2011) contends that community college online students are more likely to have applied for and/or received financial aid, indicative of lower SES. Since SES has been strongly associated with higher education enrollment and outcomes (Allen, Robbins, Casillas and Oh 2008; Walpole 2003), this suggests that SES may be an important mediating factor in online learning. In support of this, in a recent study (Wladis, Conway & Hachey, 2015), we found SES to be a significant predictor of online enrollment. However, the effect of ESL and SES on online course outcomes (rather than enrollment) remains unclear.

Theoretical Framework

The framework for this study draws on the literature on student characteristics and their contribution to student retention, as well as research on online course selection. Babad's (2001) work on online course selection suggests that students choose courses based on student characteristics, course and instructor characteristics, information available to students about the course, and situational characteristics, which include issues such as required versus elective courses, time and course load considerations. Expanding on situational characteristics, there is research which suggests that students are more likely to enroll in courses they are interested in and think are relevant to their future careers, which would suggest a stronger motivation to take major requirement courses (McGoldrick and Schuhman 2002). Other research suggests that instructor effectiveness (Lee, Yoon, and Lee 2009; Paechter, Maier, and Macher 2010) and instructor leniency (in relation to grading) (Babcock 2010) can be factors in course selection, but we attempted to mitigate for these variables by using matched courses taught by the same instructor.

PURPOSE OF THE STUDY

The purpose of this study is to assess the extent to which course-level factors (elective vs. distributional vs. major requirement; difficulty level; STEM vs. non-STEM) may be used to predict online versus face-to-face course outcomes. The reason for focusing on course-level factors is that on a practical level, institutions may find it easier and more efficient to target particular online courses for specific interventions (such as tutoring, mentoring, advisement, or extra technical help) rather than to target individual students based on a longer list of student characteristics that may not be routinely collected by college institutional research departments, and which may be difficult to track. Therefore, the following questions are addressed in this study:

a. To what extent can differences in online versus face-to-face course attrition be explained by course-level characteristics?
b. Which course-level factors are significant predictors of particularly low online course retention, compared to face-to-face retention for comparable courses?
c. To what extent does the predictive power of course-level factors remain when student-level factors are controlled in the model?

METHOD

Data source and sample

This study uses a dataset of 2,330 face-to-face and online students from a large urban community college in the Northeast who took an online or face-to-face course between 2004 and 2010. The college in this study enrolls roughly 25,000 students annually in degree-programs, with an additional 10,000 per year in continuing education programs. Over 80% of the students come from traditionally underrepresented groups in higher education, and the college has been designated as both an Hispanic serving institution and a Minority serving institution. Credit-bearing online courses were first offered at the college in 2002, and the college now offers more than 125 online courses each semester. The specific sample used in this study was chosen by making a list of all online courses taught at the college between 2004 and 2010 for which the instructor taught the same course face-to-face in the same semester, and choosing at random three online and three face-to-face courses for each instructor, so that the data consists of student records for three pairs of sections of the same course and each pair was taught in the same semester by the same instructor.

In total, the sample included 1001 records from students who took the course online and 1329 from students who took the course face-to-face. The sample included 21 different courses total, including courses in business, nursing, speech, foreign languages, social science, mathematics, computer science, and the physical sciences. Courses were taught by a total of 23 different instructors: three of the courses were taught by more than one instructor, and the rest were taught by only one instructor. In this particular college, instructors develop the online courses themselves, with oversight and training provided by the college, and if another faculty member chooses to teach the same course online, they must develop their own course materials. Students register for online courses in the same way that they do for face-to-face courses, and online courses appear no differently from face-to-face courses on a student's transcript.

For each student in each of these courses, the following data was obtained: student major (for determining whether the course was taken as an elective, distributional or major requirement); pre-enrollment G.P.A. (G.P.A. at the beginning of the semester in which the student was enrolled in the course); whether the student applied for and/or received financial aid; age; ethnicity; and gender. Information about student ESL status, whether the student received federal TANF benefits (welfare), and student placement on reading/writing tests was also requested, but sample sizes for subgroups with some of these characteristics were too small to allow for inclusion in the multilevel models that follow.

Measures

The dependent variable in this study is whether a student successfully completed the course (online or face-to-face) with a "C-" grade or higher. This standard was chosen because it is the minimum grade required for a student to obtain credit for the course in their major, or for them to receive transfer credit in the University system in this study. We use successful course completion as a measure rather than simply retention, because retention measures don't distinguish between students who receive "D" and "F" grades and those who withdraw, even though the outcome of the course for most of these students (in terms of credit toward degree and successful academic progress) is similar.

The independent variables include: course delivery method; whether the course taken was an elective, distributional or major requirement; the difficulty level of the course; and whether or not the course was a STEM course. Covariates include: G.P.A.; financial aid status; age; ethnicity; and gender.

Course delivery method was categorized as online if it was either hybrid or fully online: fully online courses are those courses for which more than 80% of the class time is spent online, and hybrid courses are those courses in which 30-80% of the class time is spent online. These definitions are those used by the college in this study, and are taken from the Sloan Consortium definitions (Allen and Seaman 2010). (In practice, fully online courses at the college are conducted entirely online, with a few meetings for orientation or testing in some cases, and hybrid courses typically meet once every 1-2 weeks.) Two analyses were run: one in which online courses were compared to face-to-face courses, and one in which fully online courses were compared to face-to-face courses (we attempted to include hybrid courses as a separate category in the latter analysis, but because they made up a relatively small proportion of online offerings at the college at the time of this study, the number was too small for the multilevel analysis to be able to be run with hybrids included as a separate category).

G.P.A. is measured as a student's G.P.A. at the beginning of the semester in which they enrolled in the course that is a part of the study sample; students who were first-time freshmen (roughly 10% of the sample) had no G.P.A., but were coded as first-time freshmen by labeling them as a separate G.P.A. category "none". G.P.A. was treated as a categorical variable, with categories chosen to match the letter grade categories: A, B, C and D/F.

Information on student financial aid was also used as an independent variable. This was a categorical variable with three values: eligible for financial aid; not eligible for financial aid; or did not apply for financial aid. Those students who did not apply for financial aid were treated as a separate group, because we suspect that this group has unique characteristics: for example, students with relatively high incomes often do not apply for financial aid because they do not expect to qualify, or students who enroll in college at the last minute do not apply because they have missed the deadlines; foreign students also do not typically apply for financial aid because they do not qualify.

Student age was also used as an independent variable. Rather than treat age as a continuous variable, we group students into two age categories: under 24; and 24 and above. The reason for this grouping is that before or after 24 years is the age typically cited in the higher education retention literature as denoting delayed enrollment (Bean and Metzner 1985; NCES 2002). We also include ethnicity and gender as independent variables. For ethnicity, we use a measure of race/ethnicity that combines both race and Hispanic ethnicity into a single variable, because this is the way the college collects race/ethnicity data.

Independent course-level variables included a student's reason for taking the course (as an elective, distributional or major requirement); the course difficulty level (100-level versus 200-level or above); and STEM/Non-STEM (science, technology, engineering or mathematics) classification . Course categorization as an elective, distributional requirement, or major requirement was based on the requirements of the student's major as listed in the college catalog: electives did not fulfill any particular curriculum requirement (other than for general elective credits); distributional requirements fulfilled a degree requirement that was not a part of the major's core curriculum; and major requirements were either explicitly required as a part of the major's core curriculum, or were elective courses in the major. Major requirements could be in the major field of study or in a related field.

Data Analyses

This analysis used multi-level logistic regression with random intercepts, with successful online course completion (with a "C-" or better) as the dependent variable; the specific class as the random effects grouping; and G.P.A., financial aid status, age, ethnicity, gender, and course-level variables as the independent variables. Course level variables (course type [elective, distribution or major requirement], course difficulty, and STEM classification) and their interaction with course delivery method were also included in the model. Initially, the model was run without covariates, and then covariates were added in a subsequent model. These analyses were run twice, comparing face to face courses with fully online and hybrid online courses grouped together, and then repeated with only fully online courses compared to face-to-face courses. The equations for the multi-level model were as follows:

First level equation: $\lambda(Y_j) = \beta_{0j} + \beta_{1j}x_1 + \cdots + \beta_{nj}x_n + \epsilon$ (1)

Second level equation: $\beta_{0j} = \alpha_{00} + \alpha_{1j}x_1 + \cdots + \alpha_{mj}x_m + u_{0j}$ (2)

Where z denotes the grouping variable, which in this case is the course taken (e.g. Math 100). Here $j = 1, \dots, p$, is an index number assigned to each group/course, where p denotes the number of groups (in this case, the number of different courses) in the sample. The $x_1, \dots, x_n$ represent the independent student-level variables (e.g. age, ethnicity), the $z_1, \dots, z_m$ denote the independent course-level variables (e.g. course difficulty level) and $\lambda(Y_j)$ denotes the dependent variable measuring the probability that a student successfully completed the course or not. In this case, $\lambda(Y) = \frac{e^Y}{1+e^Y}$ is the logit link. In these equations, α_{00} is the average value for the whole population on the dependent variable (average overall rate of successful course completion), and u_{0j} is an error term specific to each group, denoting the amount by which the mean successful course completion rate of each group varies from the predicted mean (based on the group-level characteristics). The variable ϵ is likewise a measure of how much each individual's successful course completion deviates from the predicted probability of successful course completion (based on all student and course-level characteristics); just as the variables $x_1, \dots, x_n$ take on different values for each subject, ϵ takes on different values for each subject.. The fixed effects, or the effects being modeled in this particular set of equations, are then denoted by $\beta_{0j}, \dots, \beta_{nj}$ and $\alpha_{00}, \dots, \alpha_{mj}$, while the random effects, or the effects due to factors not included in the model (typically attributed to random variation) are denoted by ϵ and u_{0j}.

RESULTS

Online versus face-to-face course outcomes

First we ran a multilevel logistic regression model with successful course completion as the dependent variable and course medium as the independent variable, and random variation by specific course controlled for using random intercepts. Course-level factors (elective vs. distributional vs. major requirement; difficulty level; STEM status), and their interaction with course delivery method, were also included as independent variables in the model (see *Table 1*). Because there were only three students of Native American/Alaskan ethnicity, we excluded these three data points from the final analyses reported here.

In this model, there was a much larger gap in successful course completion rates for courses taken as electives in the online versus the face-to-face environment, compared to those taken as major requirements, and this difference was significant. Courses taken as distributional requirements showed a similar trend, although this result was only statistically significant at the $\alpha=0.10$ level. And while lower level courses in general had a (highly significantly) lower successful course completion rate than upper level courses on average (in both online and face-to-face courses), the successful course completion rate in these courses was actually higher online than face-to-face in this model (the opposite trend as seen with upper level courses), and this difference in trends was statistically significant.

A visual representation of the different predicted probabilities by course type and delivery medium can be seen in *Figures 1* and *2* below.

Next, student-level characteristics were added (see Model 2 in *Table 1*). The significance of the course-level factors interaction with course delivery medium remained mostly unchanged: but the significance of the interaction between lower level course status and the online course medium was reduced to the $\alpha=0.10$ level, suggesting that some of that interaction may be explained by the demographic characteristics of students who choose to enroll in lower level courses online. Predicted probabilities for successful course completion based on Model 2 are substantially similar to those previously shown for Model 1 as seen in *Figures 1* and *2*.

Fully online versus face-to-face course outcomes

In the previous analysis, both fully online and hybrid courses were included in the online course medium category. However, some research has suggested that student characteristics and course outcomes in hybrid courses are more similar to face-to-face courses than fully online courses (Jaggers and Xu 2010; Xu and Jaggers 2011). To address this, the models were rerun, limiting the sample to fully online and face-to-face courses only. There were an insufficient number of hybrid courses in the sample to include them as a separate category in the analysis. The *Table 1* models were rerun with this new classification of course medium. Results for this subset of the data were substantially similar to those on the full dataset, including odds ratios, significance levels, and the values for predicted probabilities projected by the model, and are not reported here for the sake of brevity. These results suggest that limiting the analysis to fully online courses only (excluding hybrid courses) does not alter the results of the model given in *Table 1*.

Limitations

The sample used in this study comes from a single institution, and may not necessarily be applicable to all community colleges. However, the institution used for this study is large, urban and extremely diverse, and the courses and students included in this sample are likely to be representative of community colleges nationally since 82% of all community college students in the U.S. attend institutions in or on the fringe of mid- and large-sized cities (IPEDS 2003). Furthermore, because conditions regarding faculty, course requirements and institutional elements are more uniform within a single institution, focusing on a single institution rather than studying several groups of students across institutions limits threats to internal validity (Nora and Cabrera 1996).

Some of the most commonly cited student characteristics were included in the model, but there may be other student characteristics, such as ESL/Immigration status, that could shed further light on perceived differences in outcomes in different types of courses. This study also did not focus on other factors such as course design, and faculty knowledge, which may influence online course outcomes; instead variation by course (and instructor, to the extent that the same instructors taught the same courses, and there were equal numbers of sections from each instructor both online and face-to-face) was controlled for by the random effects part of the multilevel models. Further studies which include measures such as instructor's online efficacy as fixed rather than random effects may be able to shed more light on which teaching practices may be most effective in promoting positive online course outcomes, compared to what would be expected in comparable face-to-face classes.

DISCUSSION AND IMPLICATIONS

The change in odds ratios from Model 1 (course-level-factors-only model) to Model 2 (model which included student characteristics) shows that some of the differences in course outcomes observed by course-level factors can be explained by differences in student characteristics: for example, the fact that the odds ratios for both STEM and the STEM:online interaction moved closer to one when adding in the student-level characteristics suggests that the types of students who choose to enroll in STEM courses (or STEM courses online) explains some of the variation in course outcomes in these cases. Other odds ratios for course-level factors did not change significantly, but the reason for this is somewhat more difficult to interpret. Possibly student-level characteristics do not explain these differences, thus the odds ratios remained relatively stable when adding in the student-level factors into the model. However, unlike with ordinary linear regression, the degree of unobserved heterogeneity in the model will affect the magnitude of these coefficients (Mood 2010). So it is also possible that student-level characteristics do in fact explain some of the variability in course outcomes in different types of courses (which would typically decrease the magnitude of the difference between the odds ratios and one), but that the addition of the new variables also explains some of the residual variability of the course-level-only model (which would typically increase the magnitude of the differences between the odds ratios and one). If this is happening, then we would not observe much of a difference in the odds ratios for the course-level factors, because the simultaneous effects on the odds ratios of 1) the reduced heterogeneity, and 2) the correlation between course- and student-level factors, would cancel each other out.

However, even with ambiguity about the relationship between student characteristics and course-level factors, the results still reveal some important patterns: whatever role student characteristics may play in predicting online versus face-to-face course outcomes, much of the variation in online versus face-to-face course outcomes can be explained by considering course characteristics and their interaction with the online medium alone. For institutions looking for practical ways to address online course outcomes, this could be particularly useful because it suggests that interventions targeted at specific types of courses may be an effective way to eliminate or significantly reduce any differences in online versus face-to-face course outcomes. Targeting particular courses with supplementary support such as tutors, mentors, advisers, or extra technical support may be easier to implement than interventions at individual students based on student characteristics.

As an illustration, in this study successful course completion rates were 58.6% for online courses and 65.3% for face-to-face courses. If it were possible to target just the online sections taken as electives in this sample with interventions that were effective enough to raise successful course completion rates to the same rate as in equivalent face-to-face courses, then successful online course completion rates overall would have been raised to 62.1%, which would no longer be statistically significantly different from the face-to-face rate at the α=0.05 level. Courses taken as electives made up roughly 24% of the online sample, thus elimination of the gap in online versus face-to-face outcomes could have been obtained by implementing interventions among less than one quarter of online students. While there is no guarantee that any given intervention would be effective enough to raise successful course completion rates in elective online courses to the same rates as seen in elective face-to-face courses, this data simply illustrates that by targeting a smaller subset of courses which are at highest risk of dropout and failure online (compared to their expected face-to-face rates), institutions may be able to significantly improve online course completion rates overall (and may even be able to close the gap between online and face-to-face course outcomes entirely). An important next step for both research and practice would be to test interventions on particular courses (e.g. those frequently taken as electives) and to then measure the gap between online and face-to-face course outcomes.

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Table 1 Multilevel model (random effects by course), logistic regression models for successful[a] course outcomes by course delivery medium, and student and course characteristics (fixed effects odds ratios reported, with standard errors in parentheses)

		Model 1: course-level factors only		**Model 2: student-level factors added**	
	(Intercept)	3.49	***	3.40	**
		(1.18)		(1.34)	
medium	online	0.80		0.71	
		(0.18)		(0.16)	
G.P.A.	0-1.6			1.11	
(ref: 3.7-4.0)				(0.24)	
	1.7-2.6			1.01	
				(0.19)	
	2.6-3.7			1.47	*
				(0.27)	
	first-time fresh.			1.33	
				(0.30)	
financial aid	did not apply			1.33	·
(ref: not eligible)				(0.22)	
	Yes			0.93	
				(0.10)	
age	24 and over			1.68	***
				(0.18)	
ethnicity	Asian or Pacific Islander			0.97	
				(0.19)	
	Black			0.46	***
				(0.07)	
	Hispanic			0.52	***
				(0.08)	
gender	female			1.26	*
				(0.14)	
motivation	missing	0.58		0.56	
(ref: major req.)		(0.34)		(0.34)	
	dist. req.	1.12		1.14	
		(0.23)		(0.24)	
	elective	1.27		1.24	
		(0.27)		(0.28)	
	LL	0.21	***	0.25	***
		(0.08)		(0.10)	
	STEM	2.72	*	2.30	*
		(1.10)		(0.90)	
motivation:medium	missing:online	0.86		1.15	
		(0.77)		(1.03)	
	dist. req.:online	0.65	·	0.63	·
		(0.16)		(0.16)	
	elective:online	0.56	*	0.52	*
		(0.16)		(0.15)	
level:medium	LL:online	1.71	*	1.49	·
		(0.38)		(0.34)	
STEM:medium	STEM:online	0.70	·	0.71	
		(0.15)		(0.16)	
n		2,227		2,227	
AIC		2,646		2,578	

[a]Successful course outcome denotes completion of the course with a C- average or better.
· $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

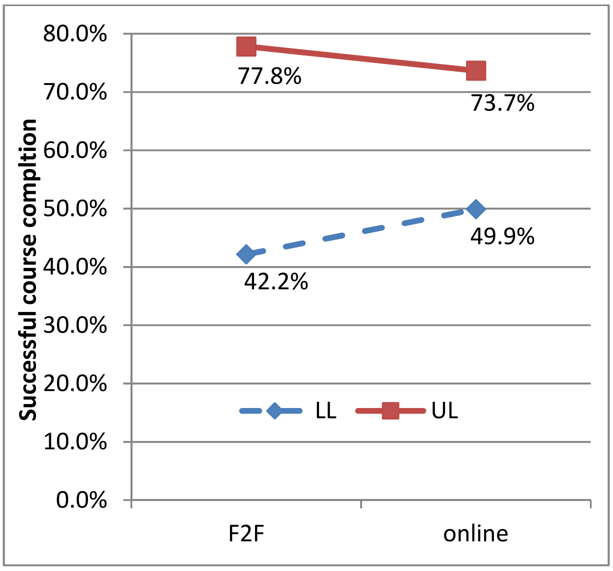

Figure 1 Predicted probabilities of successful course completion for LL and UL courses by medium, for reference group in Model 1 in *Table 1*

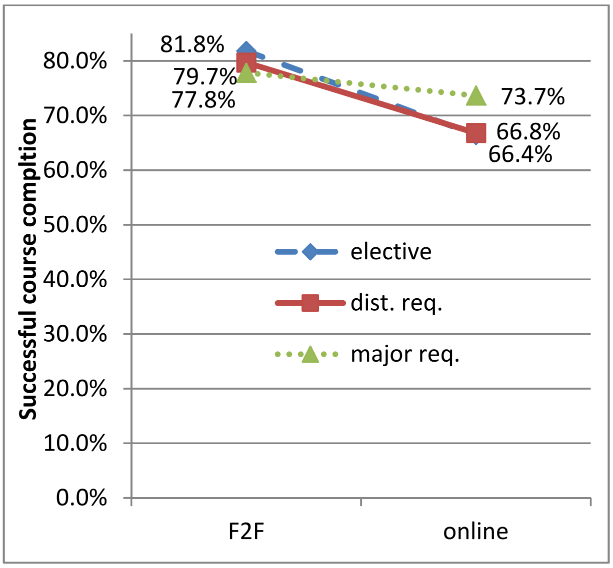

Figure 2 Predicted probabilities of successful course completion for elective, distributional and major requirements by course medium, for reference group Model 1 in *Table 1*