The Online STEM Classroom—Who Succeeds? An Exploration of the Impact of Ethnicity, Gender, and Non-traditional Student Characteristics in the Community College Context

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Abstract

OBJECTIVE: This study analyzes how ethnicity, gender and non-traditional student characteristics relate to differential online versus face-to-face outcomes in STEM courses at community colleges.
METHODS: This study used a sample of 3,600 students in online and face-to-face courses matched by course, instructor, and semester from a large urban community college in the Northeast. Outcomes were measured using rates of successful course completion (with a "C-" or higher). Multilevel logistic regression and propensity score matching were utilized to control for unobserved heterogeneity between courses and for differences in student characteristics.
RESULTS: With respect to successful course completion, older students did significantly better online, and women did significantly worse (although no worse than men) online, than would be expected based on their outcomes in comparable face-to-face courses. There was no significant interaction between the online medium and ethnicity, suggesting that while Black and Hispanic students may do worse on average in STEM courses than their White and Asian peers both online and face-to-face, this gap was not increased by the online environment.
CONTRIBUTION: These findings suggest that both women and younger students in STEM courses may need extra support in the online environment. Future research is needed 1) to explore whether factors such as stereotype threat or childcare responsibilities impact the outcomes of women in online STEM courses; and 2) to determine which characteristics (e.g. motivation, self-directed learning skills) of older students may make them particularly well suited to the online environment.

Keywords: Online learning; course retention; non-traditional students; ethnicity; gender; STEM

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Online learning has become a fundamental part of higher education and will increasingly impact graduation rates (Hachey, Wladis & Conway, 2013). Data show that the growth rates in online learning far exceed those in higher education enrollments overall; since 2010, online enrollments have increased 29% (Allen & Seaman, 2013; Community College Research Center (CCRC), 2013). This is particularly true at community colleges, which have almost universally adopted online learning, with over 60% of community college students enrolling in online classes (Parsad, Lewis & Tice 2008; Pearson, 2013).

Although online learning at the community college level has the potential to increase the access and progression of traditionally underrepresented groups in science, technology, engineering, and mathematics (STEM) disciplines, consistently documented rates of higher attrition in online courses are a cause for concern; online attrition is 30-40% in the United States, much higher than in face-to-face courses (Hachey, Wladis & Conway, 2013; Jaggars & Xu, 2010; Tyler-Smith, 2006; Xu & Jaggars, 2013). Despite this, there is a general dearth of large-scale randomized studies comparing fully online to face-to-face courses (Wladis, Hachey & Conway, 2013). The studies that are available typically have small sample sizes or look at hybrid[i] rather than fully online courses with a number of the studies only assessing final grades without accounting for attrition (Caldwell, 2006; Figlio, Rush & Yin, 2010; Mentzer, Cryan & Teclehaimanot, 2007; Scheines, Leinhardt, Smith & Cho, 2005; Waschull, 2001).

Information on success in online STEM courses is particularly critical given that half of all U.S. economic growth is attributed to STEM fields, STEM-related job openings are projected to grow exponentially in the next decade, and there currently is a severe shortage of qualified U.S. STEM workers (Babco, 2004; Lufkin, 2008; National Science Foundation, 2004a; 2004b; Terrell, 2007). Community colleges serve close to half of the undergraduate students in the U.S. (American

Association of Community Colleges, 2011). Furthermore, almost half of all bachelor's and master's degree recipients in science, engineering and health attended classes in a community college (Mooney & Foley, 2011). Community colleges have significantly more non-white minority students, female students, and non-traditional students: for example, while at four-year colleges and universities 58.1% of students had one or more non-traditional risk factors (as defined by the National Center for Education Statistics) and only 16.7% had four or more, whereas at two-year colleges 87.9% of students had one or more non-traditional risk factors, and almost one third of students had four or more (U.S. Department of Education, National Center for Education Statistics (NCES), 2012). Because community colleges have high female, minority, and non-traditional student populations, there is an increasing emphasis on building a STEM pipeline starting at the community college level for these students. Yet, there is a lack of research specific to both STEM online course outcomes and general online outcomes at the community college level. One recent study found that the gap in attrition between the same courses offered online versus face-to-face was larger for STEM than for non-STEM courses, suggesting that there may be factors in the online environment which impact STEM courses differently or more strongly than courses in other subjects (Wladis, Hachey & Conway, 2012). Without further information about the extent to which higher attrition rates are the result of the online STEM environment itself or of student self-selection, it is impossible for students, faculty, administrators, or policy makers to make evidence-based decisions about additional support to help students succeed in online STEM courses. This study addresses the gap in the literature by exploring how the online environment impacts STEM course outcomes for community college students, particularly minority, female and non-traditional students, who so often get their start at the community college and who are also least likely to successfully pursue a STEM degree.

Online Learning and Outcomes

Although little research exists specifically for community college students taking online courses, what is available suggests that online course taking may hinder student academic progress. Learning outcomes do not seem to be the issue: many studies and meta-analyses of online courses suggest no strong positive or negative effect of the online medium on learning outcomes as measured by exams or course grades (Bowen & Lack, 2012; Jaggars, 2011). Rather, research suggests that online attrition rates are significantly greater than those found in face-to-face courses, with a documented gap of 7-20 percentage points (Boston & Ice, 2011; Hachey, Wladis & Conway, 2013; Morris & Finnegan, 2008-9; Patterson & McFadden, 2009; Tyler-Smith, 2006). The attrition gap has been connected to overall academic non-success in higher education (Diaz, 2002), yet the reason for the gap in attrition rates remains unclear. The higher rate of withdrawal often found in online courses is likely the primary reason for lower rates of persistence and academic progression among community college students who take courses online (Jaggars & Xu, 2010; Wladis, Hachey & Conway, 2012). Tentative evidence suggests that taking online courses at the community college level may discourage students from returning in subsequent semesters and/or persisting toward academic goals (Jaggars, 2011; Jaggars & Xu, 2010). In particular, online attrition may impact degree completion of those who make up the majority of the community college population (first-generation college students, low-income students, female students and students of color) and who are already at greater risk of dropping out of degree programs (Bean & Metzner, 1985; U.S. Department of Education, 2009a; Zamani-Gallaher, 2007).

Online Learning and STEM Courses

There are concerns that distance education may not be suitable for STEM classes, which require hands on experimentation in laboratory settings. Some research suggests that viewing experiments is not as effective a learning tool as participating in experiments (Bernard, 2004) and that the process of trial and error is an important part of science and not adequately addressed in simulations (Morrison & Anglin, 2006). Yet, the evidence does not entirely support such arguments about the incompatibility of STEM content knowledge to online delivery methods. Several recent studies compared students in a variety of online STEM courses to students in a matched face-to-face course (Ashby, Sadera & McNary, 2011; Enriquez, 2010; Plumb & LaMere, 2011; Werhner, 2010). The results from these studies are mixed: some found higher attrition in online sections, whereas others found no difference, and some found that weaker students tended to fail or earn a "D" in the course face-to-face but withdraw online, and thus successful course completion was similar. However, these studies focused only on one particular course and have not controlled for important factors such as instructor and course type. Additionally, many of these studies did not control for student characteristics and almost all had extremely small sample sizes. Further, most involved university students rather than community college students.

There are two sets of noteworthy larger-scale studies that included STEM online courses; Jaggars and Xu (2010) and Xu and Jaggars (2011) assessed students who took online courses at community and technical colleges in Virginia and Washington State. These studies investigated student completion of online courses, particularly mathematics and English. They found that students who enrolled in online courses during their first few semesters were slightly less likely to persist in college. They also found that students in fully online courses were more likely to drop out or earn an "F" grade, even when statistical techniques were used to control for varying student factors. However, the focus of these studies was on general course patterns (for math and English specifically, rather than on STEM courses) and furthermore, these studies did not control for specific course taken. Bowen, Chingos, Lack and Nygren (2012) conducted a randomized controlled trial comparing hybrid versus face-to-face sections of an introductory statistics course and found no significant difference between course retention, grades or test scores by course delivery format. However, this study looked only at one course, was restricted to four-year colleges, and only evaluated a hybrid format. Given the state of the literature, it seems clear that more research is needed if we are to understand the effect of the online environment on STEM courses, particularly at community colleges.

Student Characteristics as a Factor in Online Attrition

Student characteristics are a factor in general online retention. In particular, gender, ethnicity, academic preparation (grade point averages [GPA] and prior experience) and certain non-traditional student characteristics (part time status, age 24 or older, low socio-economic status [SES] or receiving financial aid) have been posited as impacting online drop-out. The results of investigations of such student characteristics have been mixed (Jones, 2010). Regarding gender, some studies cite no differences, whereas others have found that females outperform males in the online environment (for a review, see Xu & Jaggars, 2013). Recently Xu and Jaggars (2013) found that female community college students did better than males in online outcomes such as course retention and grades. There are also mixed results in the literature about ethnicity and GPA. While Welsh (2007) and Aragon and Johnson (2008) found that ethnicity did not have an impact on community college online course outcomes, Xu and Jaggars (2013) report differences for Hispanic and Black students in comparison to White students. Similarly, GPA has been suggested as a significant factor affecting online course outcomes such as course retention and grades, particularly for minorities, female students, and non-traditional students (Aragon & Johnson, 2008; Morris, Wu

& Finnegan, 2005). However, recently Hachey, Wladis, & Conway (2013) found that while lower GPA may be a relatively good predictor of the likelihood of a community college student dropping out of *any* course (online or face-to-face), it was not a good predictor of the difference in attrition rates between online and face-to-face courses.

Less research exists on the impact of non-traditional student characteristics on online course outcomes, although these characteristics have been found to impact retention in the overall student success literature (Adelman, 2006; Bean & Metzner, 1985; Choy, 2002; Tinto, 1993). Specifically, SES, age and full time/part time status have been suggested as impacting online course outcomes. Many students who take courses online tend to juggle additional responsibilities and may therefore only enroll part time, an oft-cited predictor of student attrition in the face-to-face literature and strongly posited as an attrition factor in the online literature (Halsne, & Gatta, 2002; Jaggars & Xu, 2010; Xu & Jaggars, 2011a; 2011b; Yazedjian, Purswell, Sevin & Toews, 2007).

Jaggars and Xu (2010) and Xu and Jaggars (2011a; 2011b) show that online students may be more likely to have applied for or received financial aid. The report form Jaggars and Xu, combined with research linking ethnicity and outcomes to whether a student receives financial aid benefits (Allen, Robbins, Casillas & Oh, 2008; Choy, 2001; Walpole, 2003), suggests that financial aid is a factor that may impact online course outcomes. Finally, the age of the student at enrollment may have an impact. Numerous studies have indicated that students in online courses are older on average, but the data is mixed on outcomes (Colorado & Eberle, 2010; Wang & Newlin, 2002; Willging & Johnson, 2004).

Nearly three-fourths of all U.S. undergraduates are classified as non-traditional (Choy, 2002), with even higher proportions of non-traditional students [ii] at most community colleges. Recent tentative evidence suggests some non-traditional student characteristics correlate strongly with online enrollment meaning that non-traditional students tend to enroll in more online courses (CCRC 2013; Pontes, Hasit, Pontes Lewis & Siefring 2010; Layne, Boston & Ice 2013). Combined with research reporting that non-traditional students are more likely to be non-White and female (Choy, 2002; U.S. Department of Education, 1996), we posit that non-traditional characteristics are a mediating variable for differences in online outcomes by gender and ethnicity and thus may be affecting online STEM outcomes for these groups.

Theoretical Framework

The framework for this study relies on conceptual models of student retention, augmented by additional studies on the effects of various student characteristics on retention. No empirically validated model for online retention currently exists, but there are models of retention for face-to-face students, including for baccalaureate students (Tinto, 1975; 1986; 1993) and community college students and adult learners (Bean & Metzner, 1985). The few models of distance learner retention have not been widely tested (Kember, 1989,1995; Rovai, 2003). Tinto's model (Tinto, 1975; 1986; 1993), which was developed for and tested on traditional face-to-face students, is likely the most influential model of student retention. Tinto theorized that family background, academic preparation, and individual student characteristics influence student persistence through the variables of academic integration (e.g. course outcomes); and social integration (e.g. interaction with peers/faculty). However, Tinto's model is less relevant for non-traditional students because it does not give much weight to the external factors (e.g. work and family) that are more likely to impact the persistence of adult learners (Bean & Metzner, 1985; Maxwell, 1988; Park, 2007; Reuter, 2009; Tinto, 1986; U.S. Department of Education, 2009b).

Bean and Metzner's (1985) model of retention focused on nontraditional adult learners and contained three main input categories (environmental, academic, and background) that were posited to influence academic and psychological outcomes, which would in turn impact student decisions to persist. They found that grades and perception of the usefulness of the degree impacted student persistence more strongly than social integration (Bean & Metzner, 1987). This suggests that for online students, who are significantly more likely to be nontraditional (Wladis, Hachey, & Conway, 2014b), course grades and the relevance of a course to a student's degree or career plans are likely to be more important to retention than measures of social integration. Rovai's (2003) model is perhaps the model that is most relevant to online students. He combined Tinto's and Bean and Metzner's models with research on the skills and needs of online students. This model includes student characteristics, skills, and external factors as the inputs that influence internal factors that affect student persistence. However, Rovai's model is a decade old, has not been widely empirically tested, and does not address factors that might affect community college students specifically.

A number of studies have empirically tested factors that may impact online course retention, each identifying different characteristics of online students who are significantly more likely to persist or to earn higher grades: female gender, student major, being enrolled in more classes, having a higher GPA, greater self-direction/self-regulation, better time management skills, higher motivation, better academic skills, having certain beliefs about online learning and having more successful prior online course outcomes (Aragon & Johnson, 2008; Bernard, Brauer, Abrami, & Surkes, 2004; Hachey, Wladis, & Conway, 2012; Hachey, Wladis, & Conway, 2014; Hall, 2011; Hukle, 2009; Kerr, Rynearson, & Kerr, 2006; Mead, 2011; Puzziferro, 2008; Waschull, 2005; Yukselturk & Bulut, 2007). Results from these studies were very mixed, with many factors being identified as significant in some studies and not others. Furthermore, none of these studies tested whether these characteristics were significant for the online environment in comparison to the face-to-face environment; because none of these studies properly tested the interaction between these factors and the online medium in predicting course grade, it is impossible to distinguish if these factors are important in the online environment itself or if they are significant simply because they predict academic achievement generally. A few of these studies have noted this fact specifically (Shokar, Shokar, Romero, & Bulik, 2002; Waschull, 2005).

Very few studies have looked at the interaction between the online environment and other factors to predict course outcomes. This comparison is necessary to determine which factors may be salient to retention in the online environment specifically (as opposed to retention more generally in any medium). Two sets of studies have been conducted on broader groups of online and face-to-face courses and have identified some factors that may predict larger gaps between online and face-to-face course retention. In studies of community college students, we have identified that course-level factors correlate with larger gaps between online and face-to-face course outcomes (Wladis, Hachey, & Conway, 2014), and some studies have found larger gaps for ethnic minorities, men, and students with lower GPAs (Figlio, Rush, & Yin, 2010). While the models and studies cited above, along with countless others, have examined the impact of student characteristics on course and college retention, this study expands on earlier research by combining three vital aspects: exploring STEM online course outcomes among community college students who possess critical non-traditional student characteristics.

Methodology

Research Questions

This study identifies which students may be at highest risk in the online STEM environment at community colleges. In particular, it focuses on groups that have traditionally been underrepresented in STEM fields: minorities, women, and students with certain non-traditional characteristics (age, part-time enrollment, financial aid status). In particular, this study investigated the following questions:

1. Do ethnicity, gender, and certain non-traditional student characteristics (age, part-time enrollment, financial aid status) put students at greater risk of failing or dropping out of online STEM courses than would be expected given their face-to-face performance?
2. To what extent do any significant interactions identified in question 1 still hold when controlling for other covariates (specific course and instructor, college GPA at the beginning of the semester, prior online course experience, course level, course type, whether the course was taken as an elective, distributional or major requirement)?

Answers to these questions are essential if we are to determine to what extent certain groups that have traditionally been at higher risk of course and college dropout have an increased risk of STEM course dropout in the online versus face-to-face environment.

Sample

This study utilized a dataset of roughly 3,600 students from an urban community college in the Northeastern U.S. who took a STEM course online or face-to-face in 2004-2011, in order to analyze differences in course outcomes for matched online and face-to-face STEM courses with a focus on minority, female and non-traditional students. Students were chosen for the sample based on whether they had taken a STEM course that was taught both online and face-to-face by the same instructor in that semester; only fall and spring semesters were included. This was done in order to control for variation by specific courses taken and by instructor. Sections were also only included in the study if the professor had already taught online at least three times, to control for instructor inexperience in the online medium.

The community college from which the sample was taken enrolls approximately 24,000 students annually. It is designated as both a Hispanic-serving institution and a Minority-serving institution, with over 80% of the students coming from traditionally underrepresented groups in higher education. The college first offered online courses in 2002 and now offers more than 125 online courses, including STEM, Liberal Arts and Career Preparation in both STEM and non-STEM disciplines. Roughly one-quarter to one-third of the online courses offered were typically in STEM disciplines. Courses taken by students in the sample represented a wide variety of STEM courses (including but not limited to mathematics, chemistry, physics, computer science and nursing).

Variables and Methods

A multi-level binary logistic regression model was used with specific STEM course/instructor as the second level grouping factor and successful course completion, defined as completion of the course with a "C-" grade or higher (chosen because this is typically the minimal requirement for transfer of credits and for credit in the major), as the dependent variable in the model. This provides control for random variation by course/instructor combination while still controlling for fixed effects of interest by including other student level independent variables in the model. Independent variables included in the model were: course medium (online versus face-to-face); ethnicity (a combined measure of race/ethnicity, because this is how race/ethnicity is tracked within this university system); gender; age (broken into a binary variable based on whether the student was "under 24" or "24 or older"); whether the student was enrolled part-time (PT) or full-time (FT) that semester; whether the student was eligible for certain types of federal financial aid or other benefits (Pell grants or TANF benefits[iii]); the student's college GPA at the beginning of the semester; the student's prior online course experience (whether they had taken an online course at the college before, and if so, whether prior online courses were completed successfully or unsuccessfully); the level of the STEM course taken (introductory 100-level versus or 200-level or above); the type of course (career versus liberal arts); and the student's reason for taking the course (as an elective, distributional, or major requirement). Interaction with each of these independent variables with the online medium was also included in the model. To control for differences in type of STEM sub-discipline as a part of the fixed effects part of the model, we also included sub-discipline type, separated into three categories: mathematics and computer science; physical sciences; and health/life sciences.

After the initial multi-level model was run, a propensity score matching procedure was used to match online and face-to-face students in the sample on all of the independent variables. Several matching procedures were explored (e.g. nearest neighbor, genetic matching algorithms) and an exact matching procedure was used because this was the only method that yielded good balance on all covariates. Then the multi-level binary logistic regression model was rerun on the matched data. The original data had a minimum p-value of 0.0000327 over all covariates, whereas after matching, the minimum p-value was 0.7197. This matching procedure resulted in a sample of 1261 students total, of which 539 took the course online.

Results

This analysis contains two types of models: "base" models which contain course medium, ethnicity, gender, and age, along with each of the two-way interactions with course medium; and "full" models, which contain these independent variables and additionally all the other student characteristics outlined above as covariates. The odds ratios, standard errors, and significance levels for multilevel binary logistic regression (using course/instructor as the grouping factor) on both the matched and unmatched datasets can be seen for the base models and the full models in Tables 1 and 2, respectively. On the unmatched dataset, there was a significant interaction between age and the online medium; however, for the matched dataset, both gender and age had significant interactions with the online medium. After adding other student characteristics as covariates to both models, none of the interactions of student level characteristics with the online medium were significant in the unmatched dataset. For the matched dataset, both gender and age had significant interactions with the online medium. This suggests that the online medium impacts STEM course outcomes differently for women versus men and for older students versus younger students, even once other student-level variables are controlled.

[Insert Table 1 About Here]

In the base models (Table 1), which contained each of the key variables of interest (ethnicity, gender, age) and their interaction with course medium, each in a separate model without other covariates, the interaction between age and course medium was highly significant ($\alpha=0.001$) in both the matched and unmatched datasets. The interaction between gender and course medium was significant for the matched dataset only ($\alpha=0.05$), and the interaction between ethnicity and course medium was not significant for either dataset at the $\alpha=0.10$ level. Looking at the full models containing all covariates (Table 2), the interaction between ethnicity and course medium remains non-significant at the $\alpha=0.10$ level. The interaction between gender and course medium was significant for both the unmatched ($\alpha=0.10$) and matched ($\alpha=0.01$) datasets, and the interaction between age and course medium was also significant for both the unmatched ($\alpha=0.001$) and matched ($\alpha=0.01$) datasets.

[Insert Table 2 About Here]

We note also that in the full models (Table 2), the interaction between discipline and online course medium was significant for the unmatched dataset, showing that both mathematics/computer science courses and physical science courses had larger gaps between online and face-to-face course completion than health/life science courses ($\alpha=0.05$ for both). This interaction was not significant for the matched dataset because of larger standard errors, but odds ratios were similar so that the relationship revealed by the regression was similar, even if it was not significant for the matched dataset. This suggests that it may be worthwhile to investigate this difference in future studies on larger samples.

We also note that the interaction between GPA and course medium is significant for one category for the unmatched dataset (i.e., there is a significant difference at the $\alpha=0.01$ level when comparing students with a GPA of 0-1.6 to those with a GPA of 1.7-2.6). However, because the relationship between GPA and larger online versus face-to-face course completion gaps does not seem to show a consistent pattern across GPA groups (i.e., it does not seem to go up consistently or go down consistently with GPA), and because the direction of this relationship is exactly the reverse for the unmatched versus matched datasets, we suspect that this is a spurious result.

For the remainder of this section, we discuss the results of the full model based on the matched dataset. A number of studies have found that analysis conducted using propensity score matching appear to provide a better estimation of known experimental effects than regression methods which use covariates to control for unmeasured differences between the treatment and control groups (see for example, Dehejia & Wahba, 1999; Hill, Reiter & Zanutto, 2004). Because of this, we focus the bulk of our discussion on the coefficients given by the model based on propensity score matching.

Full multilevel regression on the matched dataset revealed that women were significantly more likely to succeed in a face-to-face STEM course than men, and that men and women had almost identical success rates in online STEM courses; this resulted in a significantly greater gap ($\alpha=0.05$) in online and face-to-face STEM success rates for women than for men, which can be seen graphically in Figure 1. The fact that the interaction between gender and online medium was significant reveals that the slopes visible in Figure 1 are in fact different: the slope is steeper for women than for men. We note that women did *not* do significantly worse in online STEM courses than men; rather, the two groups had equal rates of success in the online environment. However, in this sample women had significantly higher success rates in face-to-face STEM courses than men, and this advantage disappeared in the online environment.

[Insert Figure 1 About Here]

There was no significant difference in success rates for face-to-face STEM courses by age, but students under the age of 24 were significantly less likely to successfully complete STEM courses online than face-to-face, and were significantly less likely to successfully complete STEM courses online than their older peers. As a result, the interaction between the online medium and age was significant (α=0.01), with older students completing STEM courses successfully at roughly the same rate both online and face-to-face but younger students experiencing a significant drop in successful STEM course completion rates when courses were taken online. A visual representation of this trend can be seen in Figure 2, where the significant interaction tells us that the differences in slopes in this graph are indeed statistically significant.

[Insert Figure 2 About Here]

While Black and Hispanic students had worse success rates in face-to-face STEM classes (Hispanic students significantly so), this gap in successful STEM course completion was not widened online, and in fact there was no significant interaction with ethnicity and the online medium. This means that Black and Hispanic students were no more disadvantaged by the online medium in STEM courses than their White or Asian peers. Full-time versus part-time enrollment, income measures (e.g., qualifying for financial aid or federal TANF benefits), and academic preparation measures (e.g., GPA and prior online experience) were no better predictors of online versus face-to-face STEM course outcomes, as the interactions of each of these terms with the medium was not significant in the model. While a number of these factors may predict success in courses generally (e.g., students with higher GPAs tend to successfully complete both online and face-to-face STEM courses at higher rates), none of them were significant predictors of the likelihood that a student might do significantly better or worse online in STEM courses than expected given their face-to-face performance.

Limitations

This study was conducted at a single site. While the student population at this institution is very diverse and representative of many types of students nationally, it is still possible that institutional-level factors may have influenced the results. Caution should be exercised before drawing conclusions about whether these patterns hold in all higher education populations. However, we note that over 80% of all U.S. community college students attend institutions in or on the fringe of mid- and large-sized cities (U.S. Department of Education, 2002-2003), suggesting that the results of this study may be applicable to the vast majority of community college students enrolled in the U.S. Furthermore, there was an increase in internal validity in this study by limiting it to a single site (Nora & Cabrera, 1996).

In addition, because of the limits of the institutional data that were used, not all student characteristics that may affect online course enrollment and/or course outcomes could be included in the models tested here. For example, including information about a student's status as a parent and/or as a primary caretaker of small children might have accounted for some variations in online enrollment and course outcomes, and may have explained some of the differences in online versus face-to-face STEM course outcomes for women versus men. Future qualitative research which investigates some of these factors that may impact online enrollment decisions is essential if we are to better understand the findings identified in this study.

Implications

These results suggest that there may be factors associated with online course-taking which lead to women in STEM courses more vulnerable to failing or dropping out in this delivery medium. This is in contrast to results of research done by Xu and Jaggars (2013), who found that female community college students did better than males in an analysis of general online outcomes. We note that it is not at all clear whether it is the online environment itself (at least as it is currently implemented) which causes lower success rates for women in online STEM courses, or whether there are other factors which drive women who are at greater risk of failure or dropout in STEM courses sign up for online courses at higher rates. For example, it may be that the online environment itself can induce a kind of stereotype threat (Steele & Aronson, 1995) in online STEM courses for women, perhaps because women may be more negatively stereotyped as having poorer technology skills than men. Or, stereotype threat may be invoked because the lack of obvious cues about gender[iv] in the online environment may lead students to rely more heavily on preconceived notions about the gender of the instructor and the proportion of women in the class: fewer cues about gender in online courses could induce stereotype threat if women in these classes perceive themselves (perhaps incorrectly) as being the minority in the class[v], because they are unconsciously relying on stereotypes of STEM professors and students as male. Studies which investigate the way in which stereotype threat (and other factors) may play out in the online environment in STEM classes may be able to clarify the extent to which these various mechanisms are at work.

On the other hand, the online environment itself may not affect the performance of women in STEM classes; rather, there may be other factors which lead women who are at higher risk of failing or dropping out of STEM courses to take classes online at higher rates than men. For example, if women who are the primary caretakers of small children are significantly more likely to take a STEM course online, they may very well be more likely to fail or withdraw from any course, and the higher rates of failure and withdrawal that we see among women in online versus face-to-face STEM courses may simply be reflecting this difference in population. Follow-up studies which investigate students' roles as parents and primary caregivers may be able to determine to what extent these outside factors may be influencing both self-selection into online STEM courses differentially by gender, and also the outcomes of these courses.

Additionally, these results suggest that the online environment may be particularly well-suited to older students (24 and older), and that younger STEM students (under 24) may be at higher risk in the online environment. It may be that older students are more likely to possess particular characteristics that make them well suited to the online environment. For example, older students may be better at self-directed learning, which has been correlated with success in online courses in some studies (see for example, Bernard, Brauer, Abrami & Surkes, 2004; Hung, Chou, Chen & Own, 2010; Kerr, Rynearson & Kerr, 2006). These results also suggest that it may be particularly important for institutions to target younger students for particular interventions when they enroll in online STEM courses, such as additional advisement, mentoring, tutoring, or technical support.

The results of this study also suggest that non-White minority students do not do any worse online in STEM courses than would be expected face-to-face, suggesting that this achievement gap is not widened by the online environment. This provides confirmation of previous research by Welsh (2007) and Aragon and Johnson (2008), who found that ethnicity did not have an impact on community college general online course outcomes. While the need for research to better understand and uncover ways to address the STEM gap is unchanged, our findings suggest that there may be no need to tailor particular interventions for minority STEM students in the online environment specifically. Replication of these research results across a wide range of samples in multiple studies would be necessary before being certain of such a conclusion.

Tables

Table 1 Base Models: Multilevel (random effects modeled by course/instructor) Logistic Regression Models for Successful[a] Course Outcomes by Student Characteristics (Fixed Effects Odds Ratios Reported, with Standard Errors in Parentheses)

		without matching			with matching		
		ethnicity	**gender**	**age**	**ethnicity**	**gender**	**age**
	(Intercept)	4.49 ***	2.77 **	3.06 ***	10.72 ***	2.96 **	3.64 ***
		(1.67)	(0.94)	(1.03)	(4.54)	(1.11)	(1.28)
medium	online	0.65 *	0.72 *	0.41 ***	0.41 **	0.69 ·	0.29 ***
		(0.12)	(0.09)	(0.05)	(0.12)	(0.14)	(0.05)
ethnicity	Asian or Pacific Islander	1.55 *			0.88		
		(0.30)			(0.32)		
	Black	0.52 ***			0.34 ***		
		(0.08)			(0.09)		
	Hispanic	0.54 ***			0.20 ***		
		(0.09)			(0.05)		
gender	F		1.32 **			1.75 **	
			(0.14)			(0.30)	
age	24 or over			1.09			1.40 *
				(0.12)			(0.23)
medium:ethncity	online:Asian or Pacific Islander	0.82			1.08		
		(0.24)			(0.54)		
	online:Black	1.03			1.06		
		(0.24)			(0.38)		
	online:Hispanic	0.96			1.28		
		(0.22)			(0.46)		
medium:gender	online:F		0.79			0.57 *	
			(0.13)			(0.14)	
medium:age	online:24 or over			1.89 ***			2.38 ***
				(0.31)			(0.58)
	n	3,599	3,599	3,599	1,261	1261	1261
	-2 Log Lik.	-1,921	-1,970	-1,956	-851	-893	-874

AIC	3,863	3,950	3,922	1,720	1796	1758

· $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

[a]Successful course outcome denotes completion of the course with a C- average or better.

Table 2 Full Models: Multilevel (random effects modeled by course/instructor) Logistic Regression Models for Successful[a] Course Outcomes by Student Characteristics (Fixed Effects Odds Ratios Reported)

		M1: full model without matching		**M2: full model with matching**		**M3: full model with non-significant interactions removed (with matching)**	
	(Intercept)	1.75		1.51		1.67	
		(0.69)		(1.14)		(1.18)	
medium	online	0.29	***	0.55		0.46	*
		(0.09)		(0.37)		(0.15)	
ethnicity	Asian or Pacific Islander	1.81	**	1.66		1.41	
		(0.38)		(0.88)		(0.51)	
	Black	0.63	**	0.79		0.83	
		(0.11)		(0.30)		(0.23)	
	Hispanic	0.69	*	0.44	*	0.53	*
		(0.13)		(0.17)		(0.15)	
gender	F	1.49	***	2.12	**	1.92	**
		(0.18)		(0.55)		(0.48)	
age	24 or over	0.90		0.88		0.83	
		(0.11)		(0.23)		(0.20)	
enrollment	PT	0.92		0.97		1.06	
		(0.13)		(0.32)		(0.27)	
financial aid	Pell	0.86		1.09		0.81	
		(0.11)		(0.30)		(0.16)	
	TANF	0.58	**	0.51	·	0.58	·
		(0.11)		(0.20)		(0.18)	
GPA	0-1.6	0.77		0.29		0.69	
		(0.16)		(0.41)		(0.65)	
	2.7-3.6	3.00	***	2.39	***	2.49	***
		(0.42)		(0.63)		(0.49)	
	3.7-4.0	8.25	***	3.96	*	5.27	***
		(2.23)		(2.42)		(2.33)	
prior online exp.	none	1.92	***	2.83	*	2.54	*
		(0.33)		(1.31)		(0.96)	
	successful	0.77		1.09		1.97	
		(0.39)		(0.88)		(1.24)	
	unsuccessful	1.42		1,340,380		0.39	
		(0.83)		(1,815,343,441)		(0.38)	
level	UL	1.21		1.56		1.54	
		(0.58)		(1.05)		(1.03)	

type	career	8.32	7.69	*	7.60	*
		(5.02)	(6.75)		(6.64)	
motivation	dist. req.	0.57	0.72		0.72	
		(0.10)	(0.40)		(0.40)	
	elective	0.87	0.86		0.86	
		(0.15)	(0.44)		(0.44)	
	nonmatric	1.86	5.11		5.05	
		(0.64)	(6.08)		(5.98)	
medium:ethncity	online:Asian or Pacific Islander	1.12	0.77			
		(0.36)	(0.56)			
	online:Black	1.34	1.11			
		(0.34)	(0.61)			
	online:Hispanic	1.32	1.51			
		(0.34)	(0.84)			
medium:gender	online:F	0.74	0.38	**	0.46	*
		(0.13)	(0.14)		(0.16)	
medium:age	online:24 or over	1.81	2.17	*	2.52	**
		(0.34)	(0.81)			
medium:enrollment	online:PT	1.09	1.24			
		(0.22)	(0.56)			
medium:financial aid	online:Pell	1.07	0.53			
		(0.21)	(0.21)			
	online:TANF	1.12	1.40			
		(0.31)	(0.82)			
medium:GPA	online:0-1.6	4.91	6.93			
		(2.66)	(13.14)			
	online:2.7-3.6	0.93	1.11			
		(0.19)	(0.43)			
	online:3.7-4.0	1.02	1.85			
		(0.37)	(1.64)			
	online:none	1.58	0.83			
		(0.46)	(0.50)			
medium: prior online exp.	online: successful	2.09	3.64			
		(1.13)	(4.47)			
	online: unsuccessful	0.45	0.00			
		(0.28)	(0.00)			
	n	3,599	1,261		1,261	
	Log Likelihood	-1,718	-469		-476	
	AIC	3,520	1,009		1,000	

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

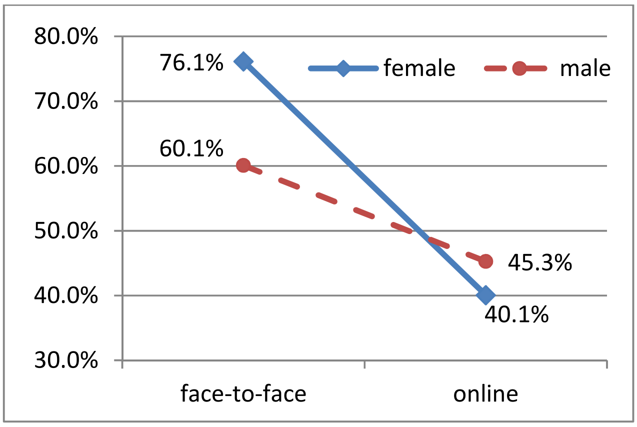

Figure 1 Predicted successful course completion by gender and medium (for reference group), based on full model with matching

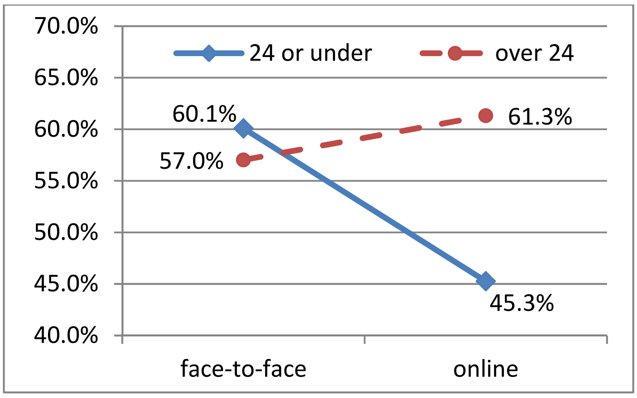

Figure 2 Predicted successful course completion by age group and medium (for reference group), based on full model with matching

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[i] Hybrid courses are courses that include both an online and face-to-face component. One common definition of hybrid and online courses, and the definition that is used at the institution in this study is based on the Sloan Consortium definitions (Allan & Seaman, 2013): 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.

[ii] There are a number of different definitions of non-traditional students that have been used in the literature. Some have defined non-traditional by age; for example, Bean and Metzner (1985) considered students over the age of 24 to be non-traditional. The National Center for Educational Statistics (NCES) considers students to be non-traditional if they possess certain risk-factors for dropping out

of college: being employed full-time while enrolled; having dependents; being financially independent; being a single parent; having no high school diploma; having delayed enrollment; or being enrolled part-time (U.S. Department of Education, National Center for Education Statistics, 1996; 2002). Some researchers have also classified students who are lower socio-economic status, who are academically disadvantaged, or who are in a minority ethnic group that has traditionally be underrepresented in higher education as non-traditional (see e.g. Jones & Watson, 1990). We use here the NCES definition.

[iii] Pell grants are awarded in the U.S. to students based on their financial need (the formula is based both on the student's household income and the costs of attendance at the institution in which they are enrolled). Roughly one-fourth to one-third of all undergraduates in the U.S. receive Pell grants each year. TANF (Temporary Assistance to Needy Families) benefits (sometimes referred to colloquially as "welfare") are federal benefits aimed at low-income citizens and permanent residence of the U.S., with families with children targeted in particular; roughly 4% of the U.S. population is typically on TANF benefits at a given time, although this rate varies by state.

[iv] While names are typically visible in online courses, gender may not be obvious from a name alone, particularly in classes which contain students from a number of different cultures/language groups. And other cues which commonly indicate the gender of the professor or other students are often less prominent online than face-to-face.

[v] *Numerical representation* (a mechanism suggesting that being a numerical minority in a group induces stereotype threat for the individuals in the minority) can be a factor in stereotype threat: for example, when female students were simply in a numerical minority when taking tests or performing other mathematical tasks, their performance was affected (Ben-Zeev, Fein, & Inzlicht, 2005; Inzlicht & Ben-Zeev, 2000).