#### An investigation of course-level factors as predictors of online STEM course outcomes

Claire Wladis Alyse C. Hachey Katherine Conway

Borough of Manhattan Community College at the City University of New York

## Abstract

This study analyzed students who took STEM courses online or face-to-face at a large urban community college in the Northeastern U.S. to determine which course-level characteristics most strongly predicted higher rates of dropout or D/F grades in online STEM courses than would be expected in comparable face-to-face courses. While career and elective STEM courses had significantly higher success rates face-to-face than liberal arts and major requirement STEM courses respectively, career STEM courses had significantly higher success rates online than would be expected, while elective STEM courses had significantly lower success rates online than would be expected given the face-to-face results. Once propensity score matching was used to generate a matched subsample which was balanced on a number of student characteristics, differences in course outcomes by course characteristics were no longer significant. This suggests that while certain types of STEM courses can be identified as higher or lower risk in the online environment, this appears not to be because of the courses themselves, but rather because of the particular characteristics of the students who choose to take these courses online. Findings suggests that one potential intervention for improving online STEM course outcomes could be to target students in specific courses which are at higher risk in the online environment; this may allow institutions to leverage interventions by focusing them on the STEM courses at greatest risk of lower online success rates, where the students who are at highest risk of online dropout seem to be concentrated.

## Highlights

- Exploration of the impact of course-level factors on online STEM course completion
- Career and elective STEM courses had higher face-to-face completion rates
- Gap between online and face-to-face outcomes was less for career STEM courses
- Gap between online and face-to-face outcomes was greater for elective STEM courses
- Differential online outcome by course type is explained by student characteristics

## **Keywords**

Online learning; course retention; career; elective; STEM

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## **1** Introduction

Higher education in the past decade has undergone a virtual transformation; online learning is now a core method of instruction at most institutions in the U.S. (Downes, 2005; Layne, Boston & Ice, 2013; Larreamendy-Joerns & Leinhardt, 2006; Sutton & Nora, 2008). Online enrollments have increased 29% since 2010, and this increase is particularly present at community colleges where over 60% of students engage in online learning (Allen & Seaman, 2010; 2013; CCRC, 2013; Parsad, Lewis & Tice, 2008; Pearson, 2011). Because of this, retention and success in the online environment will increasingly have an impact on community college graduation rates (Hachey, Conway, & Wladis, 2013).

Concomitant with the rise of online learning is a mounting need for students at community colleges to enroll in and succeed in STEM courses. Online learning at the community college level has the potential to increase access, progression and success of students in STEM disciplines, as almost half of all bachelor's and master's degree recipients in science, engineering and health have at some point attended a community college (Fast Facts, 2011; Mooney & Foley, 2011). Increasing numbers of students with expertise in STEM fields is essential to the U.S. today, as half of all U.S. economic growth is attributed to STEM fields at the same time that there is currently a severe shortage of qualified U.S. STEM workers (Babco, 2004; Lufkin, 2008; National Science Foundation, 2004; Obama, 2012; Terrell, 2007). Even for those community college students not pursuing STEM degrees, success in STEM online courses may be critical, as tentative evidence shows that withdrawal or failure in online learning early in a student's college career may impede progression towards graduation (Jaggars & Xu, 2010; Xu & Jaggars, 2011). Currently, both enrollment and outcome data denote a critical need to improve access into STEM programs and to provide assistance towards completion of STEM

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online courses at the community college level (Mooney & Foley, 2011; U.S. Department of Education, 2009; Wladis, Hachey, & Conway, in press).

This is problematic, as online course drop-out rates in the U.S. range from 30 to 40% (Tyler-Smith, 2006) and lower online retention has been connected to overall academic nonsuccess in higher education (Boston & Ice, 2011; Diaz, 2002; Jaggars & Xu, 2010; Xu & Jaggars, 2011). It is well-documented that attrition rates in online courses are significantly greater than those found for face-to-face courses, with a gap reported of 7-10 percentage points (Boston & Ice, 2011; Carr, 2000; Howell, Williams & Lindsay, 2003; Morris & Finnegan, 2008-9; Patterson & McFadden, 2009; Hachey, Wladis, & Conway, 2012). However, despite the concern about online attrition, research has lagged behind. In particular, there is a lack of research specific to both community college online learning and STEM online course outcomes (Wladis et. al., In Press). At this time, there is still not a clear understanding of the factors affecting course outcomes (CCRC, 2013; Street, 2010).

Often, community colleges' principal strategy for reducing online course failure and attrition is the early identification of students most likely to be at-risk, so that interventions can be provided (Liu, Gomez, Khan & Yen, 2007). Research has explored differences between online and face-to-face students in terms of their problem solving skills, academic and social efficacy or self-concept and empowerment levels and has found no difference in the two groups of students or in learning outcomes (Solimeno, Mebane, Tomai, & Francescato, 2007; Zhan & Mei, 2013). Studies exploring the role of prior online experience or having computer experience on learning outcomes in the online environment have been mixed (Abdous & Yen, 2010). Other work has examined the impact of student attitudes towards online learning on participation and not found a correlation (Nistor, 2013). In addition to findings of non-significant or mixed

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results,, many of these characteristics (e.g. academic self-concept, attitudes, quality of prior online experience) are difficult to measure. Therefore, a more time and cost effective method may be to examine the effect of course-level factors on predicting online outcomes, as it may be more practical for institutions to target support services at specific STEM courses rather than focusing on individual online students who have a varied list of at-risk characteristics (Wladis, Conway, & Hachey, n.d.). Despite this, no research has examined course-level factors as predictors of STEM online success, even though course-level factors have been posited as having a potential impact on course outcomes (Diaz 2002; Wladis et al., n.d.).

## 2 Methodology

## 2.1 Research Questions

This study focused on the following research questions:

- What relationship do course-level factors (e.g. level, career vs. liberal arts, elective vs. distributional vs. major requirement) have to outcomes in online versus face-to-face STEM courses?
- To what extent can any differences in successful completion rates by course be explained by the characteristics of the students who choose to enroll in different types of online STEM courses?

Framing the question of successful online STEM course completion around course-level characteristics was motivated by the fact that institutions which offer online learning are frequently looking for ways to identify which students are at higher risk of failure in the online environment so that they can advise them to take face-to-face courses instead or so that they can be targeted for additional supports online. If particular types of STEM courses could be © 2014. This manuscript version is made available under the CC-BY-NC 4.0 license: http://creativecommons.org/licenses/by-nc/4.0/

identified as being at higher risk of increased dropout/failure rates online, then from an institutional perspective, targeting these particular STEM courses for interventions aimed at increasing retention and successful online course completion could be a good approach to improving overall online STEM course completion rates and increasing progression towards graduation.

## 2.2 Sample

This study used a sample of 3,599 students at a large urban community college in the Northeast who took one of a particular set of matched STEM courses either online or face-to-face between 2004 and 2012. Students were included in the sample if they were enrolled in one of a chosen set of course sections. These course sections were chosen as follows: STEM courses were only included in the sample if instructors had taught them online for at least three semesters, to control for potential confounding effects of instructor inexperience; they were only included in the sample if they were taught by the same instructors both online and face-to-face in the same semester, so that instructors had experience teaching the course in both mediums, to control for instructor-level effects. In particular, 94 separate course sections (46 online and 48 face-to-face) of seventeen separate courses were included in the sample, including courses in astronomy, chemistry, computer science, health education, mathematics, nursing, and physics).

The college from which the sample was taken enrolls roughly 23,500 students annually in degree programs. The college has been 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. Credit-bearing online courses were first offered at the college in 2002; the college now offers more than 125 online courses each semester. Students at the college are freely allowed to select either online or face-to-face course sections

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included in this sample; each of these courses is offered in both mediums. The enrollment process for online courses is the same as for face-to-face courses except that students are required to complete an online readiness survey before they enroll in online courses, and that students with G.P.A.'s below 2.0 are not permitted to enroll in online courses. Each online course at the institution is developed individually by the instructor who teaches it, and uses the same textbooks and/or lab materials as the face-to-face version of the course, although instructors may choose individually to use whatever assignments they prefer for the online and face-to-face course sections which they teach. Class size was similar for online and face-to-face courses: an average of 20 online (95% confidence interval [10.8, 29.8]) and an average of 25 for face-to-face courses (95% confidence interval [11.6, 38.9]). Online and face-to-face courses are credited in the same way towards students' degrees, and student transcripts make no distinction between courses taken online and those taken face-to-face.

## 2.3 Variables and Methods

Binary logistic regression was used with successful course completion as the dependent variable, and with course medium (online versus face-to-face) and course level factors (level [lower level or 100-level versus upper level or 200-level and above], type [career versus liberal arts], motivation [whether the course fulfilled elective, distributional, or major requirements]) as independent variables. Information about student major was used to determine whether the STEM course that the student took fulfilled elective, distributional, or major requirements. We also included the interaction between each course-level factor and the medium in the model. Covariates for student characteristics were also included in the model: ethnicity, gender, age, part-time/full-time enrollment, financial aid status, college G.P.A. at the beginning of the semester, and prior online experience/outcomes.

We defined successful course completion as completion of the course with a C- grade or higher (since this is typically the criteria for transfer and for credit in the major). Age was coded as a binary variable indicating whether a student was "under 24" or "24 or older" at the beginning of the semester. Enrollment indicated whether the student was enrolled part-time (PT) or full-time (FT) that term. A student's financial aid status indicated whether they received federal Pell grants or federal TANF benefits ("welfare") during that semester. College G.P.A. was coded categorically corresponding to the letter grades A (90-100%), B (80-89%), C (70-79%) and D/F (below 70%) and indicated the student's G.P.A. at the beginning of the semester. A student's prior online experience was coded based on transcript data as either "no prior online experience" denoting that they had not taken an online course at the college before; "successful", denoting that they completed all prior online courses taken at the college successfully; "mixed success", denoting that they completed some but not all prior online courses successfully; or "unsuccessful", denoting that they did not complete any prior online courses successfully. By definition first-semester freshmen in this study had no G.P.A. (roughly 10% of the sample). Rather than removing them from the sample, or imputing G.P.A. for this group, we chose to include them as a separate G.P.A. category ("none"), because institutions often look for practical ways to screen students, and because being a first-semester freshman has been used by some institutions as a criterion for restricting online enrollments (for example at the site of this study, first-semester students were at one time limited as to the number of online courses in which they are permitted to enroll). A typical institution is unlikely to impute student G.P.A. in order to assess dropout risk, and therefore we felt that reporting results for these students as a separate G.P.A. category would make the results more practical for use by institutions.

First, an initial multi-level model was run, and then a propensity score matching procedure was used to match online and face-to-face students in the sample on all independent variables. While various matching procedures were explored, such as nearest neighbor and genetic matching algorithms, an exact matching procedure was used because this was the only method that yielded good balance on all covariates. The multi-level binary logistic regression model was then rerun on the matched dataset. Minimum *p*-values of 0.0000327 and 0.7197 over all covariates were obtained before and after matching, respectively, implying that the matching procedure produced excellent balance on all covariates. The matched dataset was composed of a sample of 1261 students total, of which 539 were enrolled in the STEM course included in the sample online.

## **3 Results**

Fixed effects odds ratios, standard errors, and significance levels for the initial multilevel logistic regression model without matching (Model 1), the base multilevel logistic regression model with matching but no covariates (Model 2), and the full multilevel logistic regression model with matching and all covariates (Model 3) are reported in *Table 1*.

Table 1       Multilevel (random effects modeled by course/instructor) Logistic Regression Models for Successful <sup>a</sup> STEM Course Outcomes by Course and Student Characteristics (Fixed Effects Odds Ratios Reported)									
		Model 1: base model without matching	Model 2: base model with matching	Model 3: full model with matching					
	(Intercept)	1.99 *	$2.95 \cdot (1.92)$	1.96					
medium	online	0.76	(1.92) 0.35 * (0.18)	(1.44) 0.32 (0.17)	*				
ethnicity	Asian or Pacific Islander	(0.10)	(0.10)	(0.17) 1.42 (0.51)					
	Black			0.82					
	Hispanic			(0.23) 0.54	*				
gender	F			(0.15) 1.36					
age	24 or over			(0.26) 1.28					

					(0.25)	
enrollment	PT				1.07	
					(0.27)	
financial aid	Pell				0.81	
					(0.16)	
	TANF				0.58	
					(0.18)	
G.P.A.	0-1.6				0.65	
					(0.63)	
	2.7-3.6				2.47	***
					(0.48)	
	3.7-4.0				5.27	***
					(2.33)	
	none				2.51	*
					(0.95)	
prior online exp.	successful				1.99	
	6.1				(1.24)	
	unsuccessful				0.39	
11	T TT	1 (2		1.42	(0.38)	
level	UL	1.03		1.43	1.0/	
trues		(0.78)	*	(1.12)	(0.73)	
type	career	(2, 02)	•	(5.02	(4.04)	
motivation	dist rea	(3.02)		(3.23)	(4.94)	
motivation	dist. leq.	(0.12)		(0.75)	(0.08)	
	elective	(0.13)		(0.43)	(0.42)	
	cicetive	(0.30)		(0.75)	(0.60)	
	nonmatric	2 14		2 375 780	1 027 211	
	noninaute	(1 14)		$(1\ 446\ 410\ 452)$	$(746\ 000\ 120)$	
medium·level	online UI	1 15		2.00	2.15	
incurum.ic (ci		(0.23)		(0.94)	(1.06)	
medium:type	online:career	2.75	**	1.97	2.07	
		(1.01)		(1.69)	(1.82)	
medium:		( )			( )	
motivation	online:dist. req.	0.70		1.14	1.13	
		(0.16)		(0.60)	(0.62)	
	online:elective	0.53	*	0.81	0.80	
		(0.14)		(0.49)	(0.50)	
	online:nonmatric	1.17		0.00	0.00	
		(0.74)		(0.00)	(0.00)	
	n	3,599		1,261	1,261	
	-2 Log Likelihood	-1,941		-518	-480	
	AIC	3,909		1,062	1,014	
<sup>a</sup> Successful course	outcome denotes completion	of the co	urse v	with a C- average or better	r.	

• p<0.10, \* p<0.05, \*\* p<0.01, \*\*\* p<0.001

Model 1 shows the patterns present in STEM online course outcomes before controlling for student characteristics. These results show that while career STEM courses had significantly higher success rates *face-to-face* than liberal arts STEM courses (odds ratio [OR]=4.88,  $\alpha$ =0.05),

career STEM courses had a significantly higher success rate online than would be expected given the face-to-face results, revealing a significant interaction between STEM course type and the online medium (OR=2.75,  $\alpha$ =0.01). These results can be seen graphically in *Figure 1*.

Figure 1 Predicted successful STEM course completion by course type and medium, before controlling for student characteristics



Furthermore, these results show that while elective STEM courses had slightly *higher* success rates face-to-face than major STEM requirements (OR=1.45,  $\alpha$ =0.10), they had a significantly *lower* success rate online than would be expected given the face-to-face results, revealing a significant interaction between STEM course type and the online medium (OR=0.53,  $\alpha$ =0.05). These results can be seen graphically in *Figure 2*.





There were no significant differences in successful STEM course completion when considering the interaction of course level with medium, suggesting that the level of a course does not seem to accurately predict STEM online course outcomes which are different than one might expect given the face-to-face outcomes for a STEM course.

So, these results show that while career and elective STEM courses had significantly higher success rates *face-to-face* than liberal arts and major requirement STEM courses respectively, career STEM courses had a significantly higher success rate online than would be expected given the face-to-face results, while elective STEM courses had a significantly lower success rate online than would be expected given the face-to-face results.

Adding in a number of student co-variates to Model 1 did not significantly change these results (so this model is not reported in *Table 1*). However, the propensity score matching procedure, which paired online and face-to-face students with similar characteristics, and compared their STEM course outcomes, showed no significant difference between online and face-to-face STEM course outcomes by course-level characteristics (see Models 2 and 3 in *Table 1*). This suggests that while certain types of STEM courses can be identified as higher or lower risk in the online environment (compared to what we would expect given their outcomes face-to-face), this appears not to be because of the STEM courses themselves, but rather because the characteristics of the students who choose to take these kinds of STEM courses online also affect course outcomes (for example, if higher numbers of students with high G.P.A.'s take career STEM courses online, this could cause these courses to have higher success rates online than expected). Specifically, when we compare online and face-to-face students with similar characteristics to one another in this set of STEM courses, elective courses and liberal arts courses do not seem to have any greater gap in online versus face-to-face success rates than

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major requirements and career courses respectively; this suggests that the larger online/face-toface gaps between successful course completion of elective and major requirement courses and between liberal arts and career courses is likely due to certain student characteristics that tend to be differently distributed between students who take these courses face-to-face versus those students who take these courses online.

## 3.1 Limitations

The results of this study may not necessarily be generalizable to all community colleges in the U.S. because the sample used was drawn from a single institution. Similar studies should be repeated on other samples to confirm these results. However, because the institution in this study is an urban community college, and 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), the results of this study are likely applicable to the vast majority of community colleges nationally. Additionally, the community college population used in this study is extremely diverse, therefore, students included in this sample are likely to include most groups which could be expected to be represented at community colleges nationally. Moreover, since faculty, course requirements and institutional elements are more uniform within a single institution, focusing on a single institution rather than across institutions limits the threat to internal validity (Nora & Cabrera, 1996).

The model includes some of the most commonly cited student characteristics which contribute to retention, but there may be other factors which could impact perceived differences in outcomes in different types of courses. In particular, this study did not seek to identify which particular student characteristics may lead to lower rates of successful course completion when elective or liberal arts courses are taken online; rather the study focused on controlling for © 2014. This manuscript version is made available under the CC-BY-NC 4.0 license: http://creativecommons.org/licenses/by-nc/4.0/

student characteristics, and then comparing successful completion rates at the course section level. This study also did not focus on other factors which may influence online course outcomes such as course design or faculty knowledge and experience; instead, any variation by course and instructor was controlled for by the random effects part of the multilevel models. However, we note that in one study which explored differences between online and face–to-face courses, instructor characteristics including online teaching experience, and level of academic degree, did not find that these factors had an impact on students (Solimeno, Mebane, Tomai, & Francescato, 2007). In the future, studies which include measures related to instructor influences as fixed rather than random effects may be able to illuminate practices in online teaching that could be effective in promoting positive online STEM course outcomes, compared to what would be expected in comparable face-to-face STEM courses.

## **4** Implications

The results of this study suggest that career STEM courses may be particularly well-suited to the online environment, while STEM courses typically taken as electives may need extra support in the online environment. This does not seem to be because the courses themselves are particularly more or less well-suited to the online environment, but rather because the kinds of students who sign up for online career STEM courses seem to have characteristics that make them more likely to successfully complete online courses, whereas students who enroll online in elective STEM courses appear to have characteristics that make them less likely to successfully complete an online course. In particular, targeting specific types of STEM courses with higher drops in successful course completion rates online could be an effective way of targeting higherrisk students for greater support (e.g. advisement, mentoring, tutoring or technical help) in the online environment; since from an institutional perspective, targeting support at the course rather © 2014. This manuscript version is made available under the CC-BY-NC 4.0 license: http://creativecommons.org/licenses/by-nc/4.0/

than student level is likely to be easier to implement. This could give colleges offering STEM online courses a more practical way to target students at risk in the online environment.

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