Prior Online Course Experience and G.P.A. as Predictors of Subsequent Online STEM Course Outcomes

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Highlights

- GPA and prior online outcomes separately predict online STEM course outcomes.
- Past online outcomes differ even among students with the same GPA.
- Both prior online outcomes & GPA can identify STEM students at risk online.

Abstract

This study found that G.P.A. and prior online experience both predicted online STEM course outcomes. While students with higher G.P.A.s were also more likely to have successfully completed prior online courses, prior online course experience added significant information about likely future STEM online outcomes, even when controlling for G.P.A. Students who had successfully completed all prior online courses had significantly higher rates of successful online STEM course completion at all G.P.A. levels than students who had failed to complete even one prior online course successfully. Students who had dropped or earned a D or F grade in even one prior online course had significantly lower rates of successful online STEM course completion than students with no prior online experience, even when controlling for G.P.A. This suggests that prior online course outcomes should be combined with G.P.A. when attempting to identify community college students at highest risk in online STEM courses.

Keywords: Online learning; Retention; G.P.A.; Prior online experience; Academic preparation; STEM

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1 Introduction

This paper investigates the extent to which the nature of a student's prior online course experience may be a good predictor of subsequent online course outcomes, even when controlling for general academic performance (as measured by G.P.A.) and other characteristics. In particular, this study seeks to compare subsequent online course outcomes for students with no prior online experience and students with different types of prior online course experience (students who completed all prior online courses successfully with a "C-" grade or higher; students who did not complete any prior online courses successfully; and students who completed some but not all prior online courses successfully). By controlling for G.P.A. (and other student characteristics), we seek to explore the extent to which prior online course experience and outcomes may provide information about a community college Science, Technology, Engineering and Mathematics (STEM) student's likelihood of succeeding in the online environment specifically, as opposed to their likelihood of doing well in academic courses (both online and face-to-face) more generally.

1.1 Growth of Online Learning

In response to rapid advancements in technology, shifting life styles, and expanding enrollments, higher education has embraced online learning; online learning is now a standard method of instruction at most colleges and universities (Downes, 2005; Larreadmendy-Joerns & Leinhardt, 2006; Sutton & Nora, 2008). This trend toward online learning is reflected in online enrollment growth rates that are over ten times higher than the growth in overall higher education enrollments (Allen & Seaman, 2010; 2013). Moreover, some experts assert that soon up to half of all traditional campus-based programs will be available online; the surge in online enrollment is expected to keep ascending with no plateau in sight (Allen & Seaman, 2011; 2013; Howell, Williams, & Lindsay, 2011).

The shift to online learning is particularly prevalent at the community college level. Research has established that community college students are more likely to take an online course than traditional 4-year students, and student demand for online learning opportunities at the community college level continues to rise (Capra, 2011; Horn & Nevill, 2006). In response, community colleges have almost universally embraced online learning as a way to better serve their large numbers of non-traditional students (Allen & Seaman, 2010; 2013; Community College Research Center (CCRC), 2013; Parsad, Lewis, & Tice, 2008). Almost half of all U.S. online programs are hosted by community colleges, and community colleges have the highest enrollment rates of all post-secondary institutions that offer online courses (Obama, 2012; Parsad, Lewis, & Tice, 2008; Ruth, Sammons, & Poulin, 2007). Since 2010, community college online enrollments have risen over 29%; today, over 60% of community college have taken at least one course online (Community College Research Center (CCRC), 2013; Pearson Foundation, 2011).

1.2 Attrition in Online Learning

The rapid adoption of online learning does not necessarily equate to successful course outcomes. Online attrition rates are 30-40% in the U.S. and significantly greater than what is found in face-to-face courses (Boston & Ice, 2011; Carr, 2000; Howell, Williams, & Lindsay, 2011; Morris & Finnegan, 2008-9; Patterson & McFadden, 2009; Tyler-Smith, 2006; XXXX, 2013). Online attrition has been linked to overall academic non-success in higher education, prompting the concern that attrition in the increasing proportion of online courses offered at community colleges will have an adverse impact on degree completion rates which are already unsatisfactory (Boston & Ice, 2011; Diaz, 2002; XXXX, 2013; XXXX, In Press). In particular, online attrition may impact degree completion of first-generation college students, low-income students, female students and students of color who make up the majority of community college students and who are already at greater risk of dropping out of degree programs (Bean & Metzner, 1985; U.S. Department of Education, 2003; 2009; XXXX, 2012, In Press; Zamani-Gallaher, 2007).

1.3 Community colleges and the need for STEM success

Research specifically focused on community colleges is warranted because of their unique role in U.S. higher education. Today, nearly half of all college freshmen begin their academic career at a community college (Finnegan, Morris & Lee, 2008-9; Mooney & Foley, 2011). At a cost that is slightly more than a third of four-year colleges, and with open admission policies, community colleges are a crucial point of access for minority, low income, and first-generation postsecondary students who currently remain underrepresented in STEM fields (Anderson & Kim, 2006; Attewell, Lavin, Domina, & Levey, 2006; CCRC, 2013; American Association of Community Colleges, 2013; Ginder & Kelly-Reid, 2013; Huang, Tadese, & Walter, 2000; National Science Board, 2008; Provasnik & Planty, 2008).

Moreover, the research shows that almost half of all bachelor's and master's degree recipients in science, engineering and health have enrolled in classes at a community college (Fast Facts, 2011; Mooney & Foley, 2011). Data from a six year longitudinal study found that: 1) students who entered a STEM field associate's degree program were far less likely to have attained a degree than those who began in a baccalaureate program; 2) almost half of all students entering a STEM program changed majors or dropped out of college six years later; 3) older, independent, Black or Hispanic students were less likely to attain a STEM bachelor's degree in comparison to other students; and 4) only 7.3% of students who began at a community college received a STEM bachelor's degree after six years, in comparison to 45% of students who started in a baccalaureate program (U.S. Department of Labor, 2007). This has prompted an emphasis on building a STEM pipeline starting at the community college level; both enrollment and outcome data clearly indicate a vital need to improve the gateway into STEM programs and to provide assistance towards completion of STEM courses at the community college level (Mooney & Foley, 2011; U.S. Department of Education, 2009; XXXX, 2012, In Press).

With the rise of online learning, the proportion of students taking STEM courses online at community colleges is likely growing rapidly. However, there is currently little data available on the number of STEM courses offered online, particularly at community colleges. One recent study of Washington state community college students indicated that approximately 10% of all course enrollments were in online classes, with computer science classes showing greater enrollments than the average and math and natural science classes showing less than average online enrollments (Xu & Jaggars, 2013). According to the American Association for the Advancement of Science (AAAS), the majority of STEM studies have been conducted at Research Extensive and Research Intensive universities, and there is a gap in the literature on STEM enrollment, retention and graduation at the community college level (George, Neale, Van Horner, & Malcolm, 2001). The available, limited data report on fully online programs only, not courses offered, citing that the proportion of institutions offering fully online STEM programs ranged from 17% in engineering to 31% and 33% in computer sciences and health professions and related sciences (Allen & Seaman, 2010). However, the number of community colleges offering online courses within STEM disciplines is likely much higher (XXXX, 2012, In Press).

1.3 Research on online STEM courses

There is a dearth of research on community college online learning, although some recent studies have focused on this important group of students (Jaggars & Xu, 2010; Xu & Jaggars, 2013, 2011a, 2011b). Most research on higher education, including the evaluation of online learning, is based on 4-year institutions, which because of differences in the student populations, it is difficult to generalize to community colleges (Capra, 2011; Marti, 2008). With research lagging, there is still not a clear understanding of the factors affecting online course outcomes, especially at the community college level (Community College Research Center, CCRC, 2013; XXXX, 2012, 2013, n.d. (c)). This gap in empirical knowledge is impeding effective interventions targeted to at-risk students, which Yen & Liu (2009) assert has kept attrition in online learning high at community colleges.

There is even less literature specifically devoted to the study of online STEM learning. The few research studies which have focused on STEM online learning specifically have all been at the baccalaureate or higher level, have had relatively small sample sizes and methodology issues, thus they lack generalizability and applicability to community college online STEM courses specifically (Bowen, Chingos, Lack, & Nygren, 2012; Christou, Dinov, & Sanchez, 2007; Enriquez, 2010; Griffith, 2010; Inov & Sanchez, 2006; Plumb & LaMere, 2011; Reuter, 2009; Riffell & Sibley, 2005; Smith & Ferguson, 2005). Recently, we conducted several studies at the community college level using a relatively large dataset and controlling for instructor and course taken, and we found that the gap between online and face-to-face attrition rates for the same course were significantly higher for STEM than for non-STEM courses. This points to the strong need for more research that can be used to target support services for online STEM students at community colleges. More focused research has the potential to dramatically improve STEM completion, in particular for traditionally disadvantaged and underrepresented groups in STEM fields that make up the bulk of community college student populations (XXXX, 2012, In Press).

1.4 Research on academic preparation and previous online experience

Identifying students most likely to be at-risk in the online environment, so that targeted support can be provided, is a primary strategy for minimizing online course failure and dropout (Liu, Gomez, Khan, & Yen, 2007). However, to date, no single set of variables has been determined that is able to best predict which online students are at greatest risk, although several factors have been implicated in the existing research (Street, 2010). Although not yet rigorously researched, two of those most often cited as critical in the early detection of at-risk online students are previous G.P.A. and prior online experience.

Previous academic preparation, measured by G.P.A., has been posited as a key predictor of retention in online learning (Boston, Ice, & Burgess, 2012; Diaz, 2002; Muse, 2003; Nora, Barlow, & Crisp, 2005; Rovai, 2003; for a review see Xu & Jaggers, 2013). Aragon & Johnson (2008) cite G.P.A. as a strong predictor of online outcomes: they found that students who successfully completed their online course had an average G.P.A. of 2.47 in comparison to 1.66 for non-completeters. Figlio, Rush, & Yin (2010) found significant differences in exam achievement among online and face-to face university students with lower G.P.A.; these differences were not mirrored among university students with higher G.P.A.'s. Similarly, Jaggars & Xu (2010) and Xu & Jaggers (2013) recently found that G.P.A. was positively correlated to course outcomes at community colleges in both Virginia and Washington State. However, in contrast, we found that while a lower G.P.A. may be a relatively good predictor of the likelihood of attrition in *any* course at the community college level (regardless of medium), it was not useful in predicting which students would do significantly worse in the online environment, compared to what we would expect given their face-to-face performance (XXXX, 2013). Although the current research suggests (quite logically) that G.P.A. may help to identify students who may withdraw from courses in either medium, it remains inconclusive if G.P.A. is the most effective predictor of a student's risk specifically for the online environment.

It also logically makes sense that prior experience in any learning situation would be positively correlated with future learning outcomes. However, both generally and at the community college level, there is a scarcity of empirical studies to support this assumption (Haverila, 2011; Sharpe & Benfield, 2005). The few available studies either analyze a single course, focus on senior college students, or focus on the effect of prior online experience on such factors as online interaction or student satisfaction with, or perception of, the online environment. Gosmire, Morrison, & Van Osdel (2009) found in online graduate courses that prior online experience did not affect learner interaction; Rodriguez, Ooms, & Montanez (2008) found a negative relationship between university student satisfaction with prior online experiences and online attrition; and Haverila (2011) found that prior online learning experience was a significant contributor to a learner's perceived efficiency of online learning in subsequent online courses. Previous studies have looked at whether a student has prior online course experience, or the number of prior online courses taken (Cheung & Kan, 2002; Dupin-Bryant, 2004) but none of these studies look at the ***type*** of the prior online course experience to predict future outcomes, which is the focus of this study.

Specific to the community college level, and using large multi-course datasets, we recently reported results that showed prior online course experience was strongly correlated with future online course success (XXXX, 2012, In Press). Thus, there is initial evidence that prior experience can predict subsequent online outcomes. Cheung & Kan, 2002 suggest that differences may be found among disciplines; however, to our knowledge, previous online experience has not been assessed as a predictor of online STEM outcomes specifically.

2 Methodology

This study addresses the following research question: How well do prior online course experiences/outcomes predict future online STEM course outcomes, and to what extent does this relationship hold when controlling for G.P.A.? Prior outcomes are categorized as: no prior online experience; all prior online courses completed successfully; some prior online courses completed successfully and some unsuccessfully; and no prior online courses completed successfully.

2.1 Dataset

The sample included 1,566 students who took a STEM course online between 2004 and 2012 at a large, urban community college in the Northeast. The college from which the sample was taken enrolls roughly 23,500 students annually in degree programs, with an additional 10,000 per year in continuing education 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 STEM online courses were first offered at the college in 2002 and the college now offers more than 125 online courses (including STEM, Liberal Arts and Career Preparation) each semester.

Courses included in the sample represented a wide variety of STEM courses (e.g. mathematics, chemistry, physics, computer science, nursing). Courses were included in the sample only if the instructors had taught online for at least three semesters, to exclude potential confounding effects of instructor inexperience. All courses included in the sample were taught by the same instructors both online and face-to-face, so that instructors had experience teaching the course in both mediums.

2.2 Data Analysis

Binary logistic regression was used with successful course completion as the dependent variable, and with prior online course experience, G.P.A., and the interaction between these two terms as independent variables. We defined successful course completion as completion of the course with a C- grade or higher (since this is the criteria for transfer and for credit in the major). A student's prior online experience was coded based on transcript data as:

- "no prior online experience" - no online course taken previously at the college;
- "successful" – successful completion of all prior online courses taken at the college;
- "mixed success" - completed some but not all prior online courses successfully; or
- "unsuccessful" – failed to complete any prior online courses successfully.

In addition to course grades for the online STEM course which was a part of the study and any prior online courses taken at the college, information on student race/ethnicity, gender, age, FT/PT enrollment, financial aid and TANF benefits, college G.P.A., academic major, and specific course/instructor taken were included in the model as covariates.

Information about student major was used to determine whether the online course taken fulfilled elective, distributional, or major requirements, and this categorical variable was also included as a covariate in the analysis. We note that first-semester freshmen in this study, roughly 10% of the sample, had no G.P.A. by definition. Rather than excluding these students from the sample, or imputing G.P.A. for them using a multiple imputation technique, we included them as a separate G.P.A. category ("none"). Some institutions have used being a first-semester freshman as a criterion for restricting online enrollments (for example at the study site, first-semester students were for a time, limited to one online course, a restriction since removed). Institutions will not typically impute G.P.A.'s for first semester freshmen in order to determine their risk of adverse course outcomes, so providing results for these students as a separate G.P.A. category may be more practical for use by institutions.

3 Results and Discussion

The odds ratios, standard errors, and significance levels for each factor in the binary logistic regression models are displayed in *Table 1*. *Table 1* shows two models: a base model including only G.P.A. and prior online course experience as independent variables, and a full model which includes all the course- and student-level covariates (odds ratios for specific courses in the full model have been excluded from this table for the sake of brevity). The same models were also run using multi-level modeling, with course/instructor as the grouping factor; however, because that analysis returned similar results, the simpler analysis is reported here. Initially a term representing the interaction between prior online experience and G.P.A. was included in the model, but because it was insignificant, and because the model without this interaction term had a better fit (based on AIC values), that term was removed. (The Akaike information criterion (AIC) is a measure of the relative quality of a statistical model. AIC balances the goodness of fit of the model with the complexity of the model, with lower values suggesting a better model fit.)

Table 1 Binary Logistic Regression Models for Successful[a] Online STEM Course Outcomes by G.P.A., prior online experience, and Student Characteristics (course-level effects not reported here)

		base model			**full model**		
		odds ratio	**SE**		**odds ratio**	**SE**	
	(Intercept)	0.69	(0.08)	**	2.34	(0.91)	*
ethnicity	Asian or Pacific				1.95	(0.48)	**

	Islander						
	Black				0.84	(0.15)	
	Hispanic				0.91	(0.17)	
gender	F				1.18	(0.17)	
age	24 or over				1.62	(0.23)	***
enrollment	PT				0.95	(0.14)	
fin. aid	did not apply				0.08	(0.07)	**
(ref = none)	Pell				0.95	(0.14)	
	TANF				0.63	(0.13)	*
motivation	dist. req.				0.46	(0.13)	**
(ref = major req.)	elective				0.77	(0.19)	
	nonmatric				1.74	(0.74)	
GPA	0-1.6[b]	3.53	(1.56)	**	4.02	(2.03)	**
	2.7-3.6	3.76	(0.50)	***	2.78	(0.42)	***
	3.7-4.0	8.65	(1.89)	***	8.56	(2.11)	***
	none	2.96	(0.61)	***	3.30	(0.85)	***
prior exp.	mixed success	0.64	(0.15)	·	0.77	(0.21)	
(ref = none)	successful	1.27	(0.22)		1.66	(0.32)	**
	unsuccessful	0.52	(0.11)	**	0.65	(0.16)	·
	n	1,566			1,566		
	R^2 (Nagelkerke)	0.17			0.41		
	-2 Log Likelihood	-917			-741		
	AIC	1,850			1,553		

[a] Successful course outcome denotes completion of the course with a C- average or better.
[b] We note that students in the lowest G.P.A. category 0-1.6 seemed to have better outcomes than students in the next category 1.7-2.6; however, at the research site, students with G.P.A.'s below 1.7 are typically not permitted to take online courses, so the students in the 0-1.6 G.P.A. category are not only small in number, but also not representative of students in this G.P.A. group more generally, and thus the results of this study are likely not generalizable to students in this G.P.A. category. For this reason, information about students in this G.P.A. group has been excluded from the figures that follow.
· $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

In these models, both G.P.A. and prior online experience are significant predictors of successful online STEM course completion, even when we control for course- and student-level factors. Students with higher G.P.A.'s were more likely to successfully complete online STEM courses. But even when comparing students in the same G.P.A. category, students with successful prior online experience were more likely to successfully complete subsequent online

STEM courses than students with no prior online course experience, and students with mixed prior online course success or unsuccessful prior online course experiences were less likely to successfully complete an online STEM course than students with no prior online course experience.

Visual illustrations of these patterns can be seen in *Figures 1* and *2*. *Figure 1* gives the predicted probabilities of successful online course completion based only on G.P.A. and prior online course experience (base model), whereas *Figure 2* displays the predicted probabilities of successful course completion for members of theses subgroups, once other course- and student-level covariates are controlled (full model).

Figure 1 Predicted successful online STEM course completion by GPA and prior online experience, base model (*Table* 1) without interaction

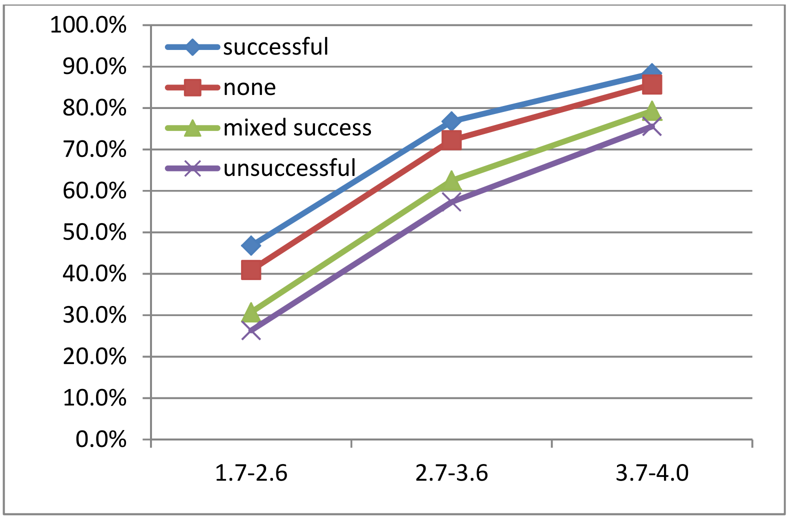
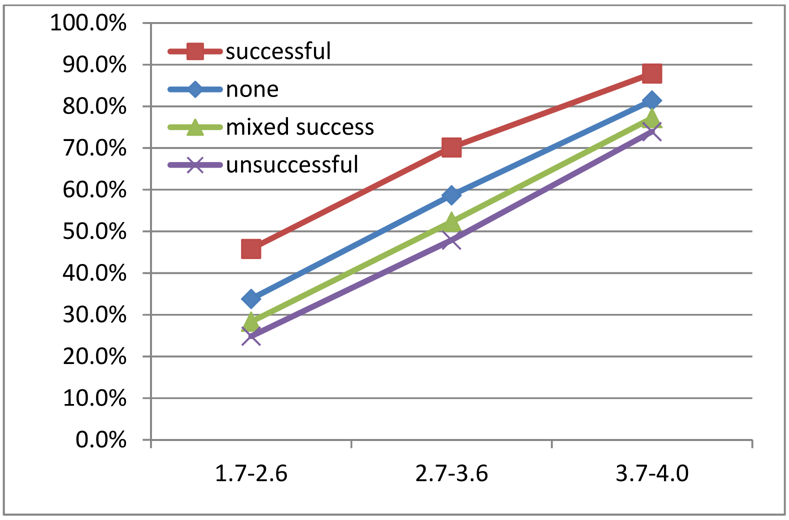


Figure 2 Predicted successful online STEM course completion by GPA and prior online experience, full model (*Table* 1) without interaction



These figures show that even when controlling for G.P.A., students who had not successfully completed any prior online courses ("Unsuccessful") had the lowest rates of future successful online STEM course completion. Successful course completion was followed in increasing order by students with mixed prior online experience ("Mixed"), students with no prior online course experience ("No exp."), and students who had completed all prior online courses successfully ("Successful"). The *Successful* students had significantly higher rates of successful online STEM course completion at all G.P.A. levels than *Mixed* students or *Unsuccessful* students, and *Unsuccessful* students had significantly lower rates of successful online STEM course completion than students with no prior online experience. This suggests that students in all G.P.A. categories are at much higher risk of failing or dropping out of future online STEM courses if they have taken online courses before without successfully completing them. To test the significance of the differences in online STEM course outcomes by prior online course experience (when G.P.A. and other covariates are controlled), we ran a set of planned pairwise comparisons by rotating the prior online experience reference group through all possible values in the base and full binary logistic regression models in *Table 1*. The results of these planned pairwise comparisons can be seen in *Table 2*.

Table 2 Planned pairwise comparisons for differences in rates of successful online STEM course completion by prior online course experience/outcomes, while controlling for G.P.A. and the other student characteristics given in *Table 1*

		p^a base model		p^a full model	
successful	none	*NS*		0.0094	**
successful	mixed	0.0104	*	0.0117	*
successful	unsuccessful	0.0006	***	0.0011	**
none	mixed	0.0513	•	*NS*	
none	unsuccessful	0.0029	**	0.0796	•
mixed	unsuccessful	*NS*		*NS*	

[a]*p*-values are taken from binary logistic regression models (*Table 1*) by rotating through the reference value for prior online course experience as needed to obtain all planned pairwise contrasts

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

These results suggest that most of the differences in the intercepts of the lines given in *Figures 1* and *2* are significant, and that the different types of prior online course outcomes/experiences do seem to be significant predictors of differences in future online course outcomes.

One question of interest following these results may also be to determine to what extent students with different G.P.A.'s actually fall into the different prior online experience groups. To what extent are there students from each G.P.A. category in each prior online experience group? *Table 3* and *Figure 3* display the raw numbers and relative percentages of students from each G.P.A. category in each prior online experience group. (Again, results for the G.P.A. category 0-1.6 are not truly representative, as students with a G.P.A. below 1.7 are not typically permitted to enroll in online courses at the study site.)

Table 3 Numbers of students in each G.P.A. category by prior experience group

	none	unsuccessful	mixed success	successful
0-1.6	23	3	0	0
1.7-2.6	253	60	45	51
2.7-3.6	522	41	48	136
3.7-4.0	178	2	4	45
total	976	106	97	232

Note: This table does not include first-semester freshmen, who do not yet have a G.P.A.

Figure 3 Percentage of students from each G.P.A. group in each prior online experience group

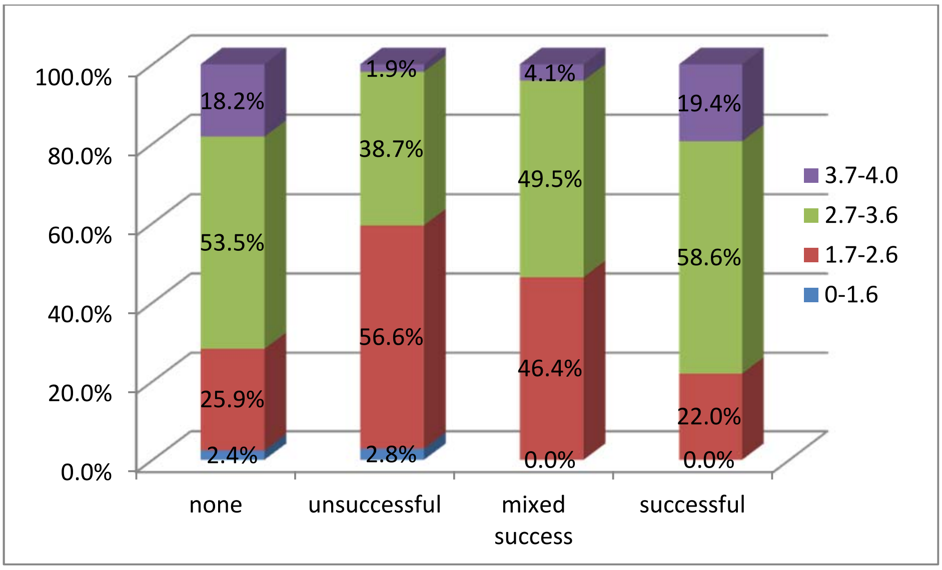


Table 3 and *Figure 3* show that while it is true that the number of low-G.P.A. students goes down as prior online success goes up, and vice versa with high-G.P.A. students, for students with G.P.A.'s between 1.7- 3.6, there is a wide distribution of students with each kind of prior online experience/outcomes. This suggests that these results are particularly applicable to the majority of students with G.P.A.'s in the mid-range, whose online course outcomes can be better predicted if prior online experience/outcomes are taken into account in addition to G.P.A.

These results suggest that students who have lower G.P.A.'s (below 2.7), and those students who attempted but failed to complete at least one prior online course with a C- or higher, are at elevated risk of dropping out or earning a “D” or “F” grade in future online STEM courses. In particular, even after controlling for G.P.A., prior online course experience/outcomes are still a significant predictor of future online STEM course outcomes. Students with higher G.P.A.'s were as expected more likely to successfully complete an online STEM course with a “C-“grade or better, but the addition of prior online course experience/outcomes as a variable added important information about the probability of successful online STEM course completion. The two variables, G.P.A. and prior online success significantly improved the predictive power of the model.

The outcomes of prior online courses taken, not simply having had prior experience online, is important in predicting future online STEM course grades and withdrawal. Analysis in which all students with prior online course experience were grouped together did not show significant differences in course outcomes for students with prior online course experience versus those with none. It was only when the *type* of prior online course experience was included in the model were there clear differences: when controlling for G.P.A., students who successfully completed all prior online courses with a “C-“ grade or better were more likely to successfully complete a subsequent online STEM course than students with no prior online experience. Both of these groups of students were more likely to successfully complete a subsequent online STEM course than students who had failed, earned a “D” grade, or dropped out of at least one prior online course.

3.1 Limitations

Because this study was conducted at a single site, this limits the external validity of the results, and as such these types of studies should be repeated in other contexts to confirm the generalizability to other populations. However, the high level of student diversity at this site, and that fact that over 80% of all U.S. community college students attend institutions in or on the fringe of mid- and large-sized cities (National Center for Education Statistics (NCES), 2002-3), suggest that these results may be applicable to the vast majority of community college students in the U.S. Furthermore, limiting this study to a single site increases internal validity (Nora & Cabrera, 1996).

Another limitation of this study is the small number of students in the very low and very high G.P.A. ranges. The power of some of the statistical tests in this study was likely impacted by the small numbers of students in some of the subgroups. Further studies with larger numbers of students in these G.P.A. groups may shed more light on some of the observed trends which seemed to be non-significant.

Furthermore, while this study explores some of the factors which may help us to predict future STEM course outcomes for students who take courses online, it does not explore them all. It is likely that models that combine the factors included in this study with more student- and course-level factors could produce an even more accurate predictive model of future online STEM course outcomes.

4 Implications

This research suggests that looking at outcomes in prior online courses, in addition to G.P.A. (which tends to be heavily weighted toward face-to-face course outcomes and which often does not include information about withdrawal), gives a much more precise way of predicting how students might fare in subsequent online courses. For example, some institutions (such as the one evaluated in this study) use G.P.A. as a criterion to determine which students may enroll in online courses, without attending to the fact that, as shown in this paper, outcomes in prior online courses give a significantly more precise prediction of online course outcomes than G.P.A. alone. As an illustration, *Figure 2* shows us that the rates of successful online course completion can differ by approximately 22 percentage points within the same G.P.A. group, depending on prior online experience. For example, students with an "average" G.P.A. between 2.7-3.6, had successful online completion rates ranging from 47.9-70.2%, depending on the type of prior online experience (no prior online courses completed successfully with a "C-" or higher; some prior online courses completed successfully; no prior online experience; all prior online courses completed successfully).

4.1 For Research

This research suggests that prior online course outcomes (or a lack of prior online course experience) add predictive information (on top of whatever information is provided by G.P.A. alone) about a student's likelihood of completing subsequent online STEM courses successfully. However, the mechanism by which this works is not clear. One possible explanation is that some students are better suited than others to the online environment,and a student's first online course outcome is simply a signal which indicates into which group a student falls. Another possible explanation is that a student's first online experience is a critical one that determines a student's attitude towards future online courses as well as the student's adaptability to challenges, mastery of material and perseverance in those courses,. Future research is needed to determine which of these factors may be at play, since the most promising potential course of intervention for these students would be different depending on which mechanism may be at work.

4.2 For Practice

This study showed that the outcome of prior online courses (or lack of online experience) was a significant predictor of subsequent online outcomes even after controlling for G.P.A. Institutions should therefore be cautious about using G.P.A. alone (without additional information about a student's prior online course-taking) to predict student outcomes in the online environment. As *Figure 2* shows, subsequent online outcomes can vary widely even within the same G.P.A. group, depending upon prior online course outcomes.

The results of this study also indicate that 1) students with lower G.P.A.'s, and 2) students who (regardless of G.P.A.) were unsuccessful (i.e. did not complete the course with a C- or better) in a prior online course, are at highest risk of failing or dropping out of subsequent online STEM courses. Therefore institutions may be able to raise online STEM success and retention rates by providing these students with additional supports in the online environment. Depending upon which mechanisms explain the patterns revealed in this study, different potential approaches to improving online attrition in STEM courses may be more appropriate. If, for example, poor prior online outcomes are an indicator of a student's lack of suitability for the online environment, then the most effective course of intervention for these students may include advising them to take a face-to-face course or assisting them in acquiring the skills needed to succeed online. In particular, institutions could provide them with particular assessment and follow-up training to determine the skills or behaviors they need to succeed online and then help them to develop these skills. More research would certainly be needed in order to develop valid screening instruments and effective training programs for these skill sets. On the other hand, if it is the actual experience in a student's first online course which then predisposes them to succeed or fail in subsequent online STEM courses, by impacting their attitudes about online courses and their own ability to succeed in that environment, then the most promising intervention may be for institutions to pay special attention to students enrolled in their first online course. To maximize the chances of successful course completion for students who are known to have unsuccessful prior online course experiences, extra advising and other training may be able to change student disposition towards the online environment (although more research would be needed to determine which types of advisement and training might be able to effectively accomplish this).

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