Is the Second Time the Charm? Investigating Trends in Online Re-enrollment, Retention and Success

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Abstract

Online education is becoming an increasingly important component of higher education. The Sloan Foundation 2010 Survey of Online Learning reports that more than 30% of all students take at least one online course during their college career. Because of this, attention is now turning to the quality of student outcomes that this instructional method provides. However, there is a huge gap in empirical investigations devoted to the link between technology and performance indicators such as grade performance, re-enrollment and course completion (Nora & Plazas Snyder, 2008). This study found that prior online course experience is strongly correlated with future online course success. In fact, knowing a student's prior online course success explains 13.2% of the variation in retention and 24.8% of the variation in online success in our sample, a large effect size. Students who have not successfully completed any previous online courses have very low success and retention rates, and students who have successfully completed all prior online courses have fairly high success and retention rates. Therefore, this study suggests that additional support services need to be provided to previously unsuccessful online learners, while students who succeed online should be encouraged to enroll in additional online courses in order to increase retention and success rates in online learning.

Key Words: Online Learning, Student Retention

Introduction

With President Obama's recent call for more college graduates and enrollment exploding today, online education provides a low cost and convenient method of expanding instructional delivery. The current generation of college students have embraced technology in higher education, as evidenced by enrollment in online classes growing by one million students from 2009 to 2010, representing the largest ever year-to-year increase in the number of students studying online (Allen & Seaman, 2010). The popularity of online education is further seen in that the 21% growth rate for online enrollments far exceeds the 2% growth in the overall higher education student population, with at least 5.6 million students enrolled in online courses in the fall of 2009. Further, the Sloan Foundation 2010 Survey of Online Learning reports that more than 30% of all students take at least one online course during their college career. And, this trend is expected to keep growing. Given its popularity, online education is becoming an increasingly important component of higher education.

In particular, community colleges have recognized the changing educational and life-style needs of today's higher education students. Online education aligns with community colleges' mission of open access by helping such institutions provide a wide range of programs to greater proportions of students. As early adopters, by 2007, 97% of community colleges offer online courses (Parsad & Lewis, 2008). In line with the national trend towards greater access through online learning, the community college in this study developed a faculty-driven online learning program in 2001. Similar to national trends, the online program at the College has shown a steady growth rate, with online enrollment from 2003 to 2010 more than five times the rate of overall face-to-face enrollment.

With the rapid growth of online enrollment at the community college level, and the College in this study in particular, attention is now turning to the quality of student outcomes that this instructional method provides. Given consistently reported higher attrition for online courses in comparison to face-to-face courses across colleges and universities in the U.S. (Carr, 2000; Hachey, Wladis & Conway, *In Press;* Morris & Finnegan, 2008; Tyler-Smith, 2006), a growing concern is identifying factors that may be affecting student retention in online courses in order to

better target student support (Aragon & Johnson, 2008). Raymond & Blomeyer (2007) assert that it is vital that online education programs use their student data to make program improvement. Yet, Nora & Plazas Snyder (2008) contend that there is a huge gap in the research literature devoted to empirical investigations on the link between technology and performance indicators such as grade performance, re-enrollment and course completion.   In particular, there is little knowledge of enrollment patterns related to online courses (Frankola, 2001; Maxwell et al., 2003). To answer this call, this study assesses recent trends in student enrollment and outcomes at a large, urban community college.

Background and Literature Review

The community college in this study is located within the largest urban population in the United States. It enrolls approximately 23,500 students in degree-programs and over 10,000 more in continuing education programs.   The College represents a diverse student body, with enrollees coming from over 150 countries around the world. The majority of the College's student population (80%) belong to groups historically underrepresented in higher education, with 37% of the student body African-American, 33% Hispanic, 14% Asian, and 16% Caucasian. In addition, about two-thirds of the student body at the College is female. The College currently offers an online Associate's Degree in Liberal Arts and has approximately 100 online courses in both liberal arts (82%) and career majors (18%).

In an earlier research study looking at student outcomes in online learning at the College, we identified a pattern (a trend not replicated in face-to-face courses) of higher online attrition rates in the fall than in the spring of the same academic year (See *Figure 1*.):

FIGURE 1: Gap Between Online and Face-to-Face Attrition Rates
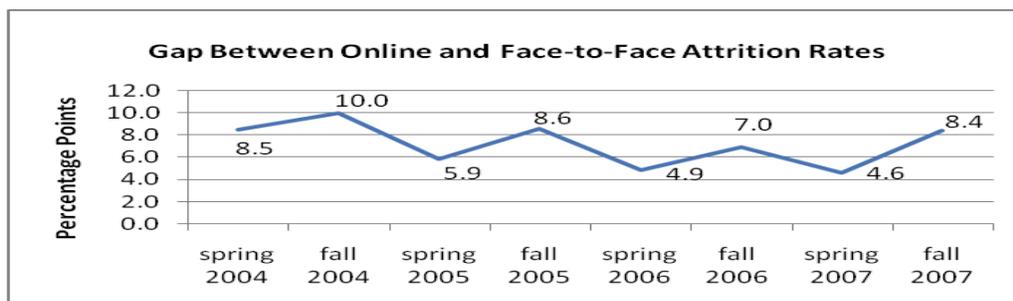
In two of the three years in which data were analyzed, this gap was statistically significant, and in the third year, while not statistically significant, the *P*-value of the *z*-statistic was still relatively close to the threshold (5%) for significance, at 6.81% (See *Table 1*).

TABLE 1: Gap in Attrition Rates between Online and Face-to-face Courses, Compared by Semester

	fall 2004	spring 2005	fall 2005	spring 2006	fall 2006	spring 2007
online	23.9%	20.1%	21.6%	19.9%	23.4%	23.2%
face-to-face	13.9%	14.2%	13.0%	15.0%	16.4%	18.6%
Gap[†]	10.0	5.9	8.6	4.9	7.0	4.6
z-statistic[††]		-2.19		-2.45		-1.49
P-value		0.0143		0.0071		0.0681

[†]between online and face-to-face attrition (in percentage points)

[††]comparing the gap between online and face-to-face courses in the preceding fall semester to the given spring semester

There is a great deal of data that shows that no significant differences should be expected regarding the effectiveness of online learning compared with face-to-face learning (Russell, 1999). Therefore, this data pattern raises the key question: Why is there a significant and consistent difference between fall and spring completion rates in online courses that is not mirrored in face-to face attrition rates? Carr (2000) has linked rates of drop-out with student perception. Given the significant yo-yo attrition pattern observed in the data, it may be that

students' perceptions unique to the online environment are affecting student outcomes between semesters.

Muilenburg & Berge (2005) report data which suggest perceived barriers to online learning drop after completing just one course, with fear of the unknown appearing to be an important factor. Moreover, they found that as the barriers perceived decrease, the likelihood of taking and succeeding in a future online course increases. This is similar to the findings of Dupin-Bryant (2004), who reports that prior educational experience and prior computer training may be important characteristics of those who complete online courses and those that do not. Based on this work, we hypothesize that the fall semester serves as a kind of exposure/ acclimation period for many students who are new to the online learning environment: students who struggle in and withdraw from online courses in the fall learn from this experience and adjust their expectations and work habits, and then re-enroll in online courses in the spring, this time better prepared for the experience, so the online student body in spring has more experience with the online learning process than it did in the fall. One piece of data that speaks in favor of this hypothesis is a finding from an internal student withdrawal survey: In the spring of 2008, 51 of the 218 students who withdrew from online courses in that semester responded to a survey conducted by the College's Academic Advisement Center. In the survey, 92.5% of the students responded that they would be interested in taking an online course again (despite their decision to withdraw that semester), which suggests that students who withdraw from one online course probably do take another one in subsequent semesters. Students who take online courses in the spring may have more online experience, and even more prior online success than those who take them in the fall, which could explain the patterns of attrition gap by semester.

Research suggests that novice online enrollees are significantly less confident than experienced online enrollees that they can complete and get a good grade in online courses (Dobbs, Waid & del Carmen, 2009). Further, novice users have been shown to be less satisfied with their skills and are more likely to become stressed when encountering problems (Eastin & LaRose, 2000; Morris & Finnegan, 2008-9). Additionally, level of student skill has been connected to participation in online activities (Alexander, 2001; Dupin-Bryant, 2004). Even if students are familiar with computing, they may be novices at learning and communicating in an online higher

educational setting. This can affect the amount of effort and persistence they put forth when faced with obstacles, and thus, affect attrition rates. On the other hand, students' confident in using online learning technologies have been shown to perceive significantly fewer barriers for social interaction, administrative/instructor issues, motivation, and time and support for studies in the online environment than those students who are unsure of their skills (Muilenburg & Berge, 2005).

The noted trend in the data, then, may relate student outcome to levels of Internet self-efficacy. Internet self-efficacy is defined as the belief that one can successfully perform the distinct sets of behaviors required to establish, maintain and utilize the Internet, over and above basic personal computer skills. It has been positively correlated to Internet usage, prior experience, and outcome expectancies (Eastin & LaRose, 2000). Internet self-efficacy has been shown to be essential to overcome the fear many novice users experience in remote computing situations (Staples, Hulland & Higgins, 1998). Successful navigation of the online course environment requires a new skill set that may seem daunting to the novice user (McLoughlin & Marshall, 2000) and low Internet self-efficacy could be contributing to high attrition rates in the fall for novice online enrollees. If our hypothesis that students who drop out in the fall semester may be subsequently re-enrolling and succeeding in the spring semester is substantiated, then this suggests that specific support services may need to be directed toward novice online learners and that online programs in higher education may need to direct their resources to a higher level of orientation and student support in the fall semester, when more novice online students are likely to enroll.

Therefore, the objective for this study is to determine if there are patterns of experience with and/or exposure to online learning courses that lead to improved student retention (lower attrition). Based on this, our specific research questions are:
1. Does the visible trend of higher attrition rates in the fall compared to the spring persist when instructor and course type are controlled?
2. Is previous online exposure alone (whether courses are completed successfully or not) a predictor of future success in online courses, or is it only predictive of future online success when prior online courses are completed successfully

Methodology

This study utilizes data provided by the College's Office of Institutional Research. Specifically, two different kinds of data were requested – one set to assess differences in online and face-to-face success rates, and one set to analyze the effect of prior online course experience and success on current online success and retention. For the purpose of this study, enrollment in an online course is defined as any course in which at least 80% of the course content is delivered online.

For the assessment of online vs. face-to-face success rates based on semester, retention data were obtained for 258 course sections, half of which were taught online and the other half of which were taught face-to-face. The online course sections in this data set were derived from a larger pool in the following way: first, data were obtained for all online courses taught at the College from 2004-2010 in either the fall or spring semester. Next, the sample was reduced to include only those course sections for which an instructor taught the same course both face-to-face and online in the same semester. The sample was further limited to only those courses for which there were at least three semesters during which pairs of online and face-to-face course sections were taught by the same instructor.   A random number generator was then used to reduce the number of sections so that for each course, there were exactly three pairs of online and face-to-face sections, with each pair taught by the same instructor in the same semester. Finally, in order to ensure that the sample was representative of the breadth of the college's online (and insofar as possible, face-to-face) course offerings , the sample was reviewed and reduced so that no one course by discipline, level of difficulty or instructor was disproportionately represented in the sample. The use of this specific sample allowed control for the instructor, semester, and exact course taken, so variation in retention rates could be reduced and potentially confounding variables removed from the equation.

For the assessment of the affect of prior online course experience and success on current online success and retention, data was collected for 61 course sections, all of which were taught online by instructors who teach the same course face-to-face and who have been teaching online for at least three semesters. Again, a wide distribution of courses that covered both upper and lower level courses in career, liberal arts, STEM (science, technology, engineering and mathematics)

and non-STEM disciplines, and which covered a wide range of course subjects were included in the sample. A random number generator was used to reduce the number of sections until there were exactly three sections for each course.

For every student enrolled in the courses in this sample a list of previous online courses taken (with final grades) and the final grade in the course (including withdrawal status) were obtained. Student data were provided without identifiers and with unique identification numbers. This resulted in a total data set of 962 participants. Basic distribution of the data can be seen in *Table 2* below.

TABLE 2: Distribution of the Data (N = 880)

| Variable	Categories	Frequencies	%
Previous Online Experience	prior online exp[†]	232	26.3%
	no online exp.	648	73.6%

[†]includes successful and non-successful previous experience

Results and Discussion

Question 1: *Do the differences in fall and spring semester attrition persist when instructor and course type are controlled?*

The first question analyzed in this study is whether or not the pattern of higher online vs. face-to-face attrition ratios seen in fall vs. spring (*Figure 1*) persisted if the analysis is restricted to a sample that matches each online course section with a face-to-face section of the same course taught by the same instructor in the same semester. The overall trends for 2004-2010 are displayed in *Figure 2*.

FIGURE 2: Attrition Rates between Matched Online and Face-to-Face Sections
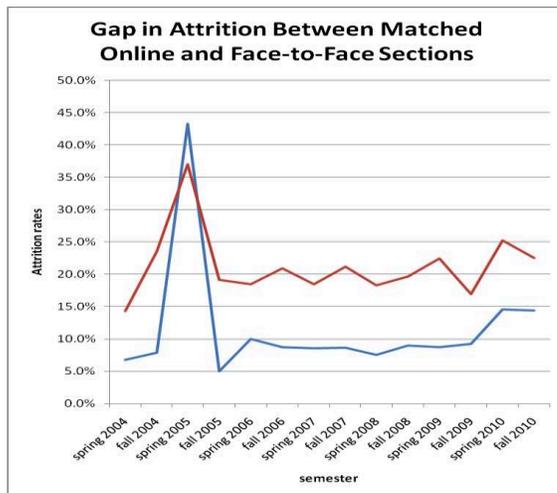
Visually inspecting the data, the trend of larger gaps between online and face-to-face attrition in fall vs. spring is apparent from spring 2004 through 2008; however, in 2009 and 2010, this trend seems to be reversed. In 2009, there is a reasonable explanation: in spring 2009, a change to the way the online course management system was managed at the university created problems with the online system that repeatedly led to the system being down and, therefore, inaccessible to both students and faculty. The problems persisted through at least mid-March, leading to an unusually high student withdrawal rate that semester compared to other semesters; in addition, in fall 2009, the college began a new procedure for student registration for online courses which required that students complete a number of new steps to register (previously students could register for online courses online in the same way that they register for face-to-face courses). Because it was suddenly much more difficult for students to register for online courses, online enrollments dropped so that class sizes were smaller (and smaller class size has been linked to lower attrition (Rovai, 2002). In addition, the student population in 2009 was likely comprised of more technically savvy, persistent students who were able/ willing to navigate a relatively new and complex registration system.

Looking in particular at the average attrition in spring vs. fall semesters, it is apparent that the average spring attrition is in fact lower than the average fall attrition (see *Figure 3*).

FIGURE 3: Average Attrition by Course Delivery Method and Semester2004-2010
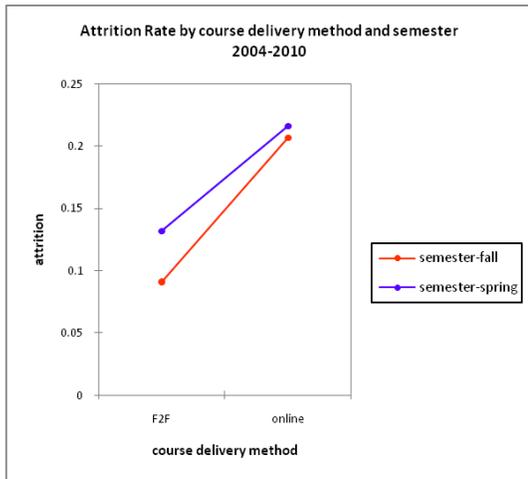
Is this difference statistically significant? In order to answer this question, an ANOVA analysis was run with the attrition rate as the dependent variable, and semester type (fall vs. spring) and course delivery method (online vs. face-to-face) as the independent variables. We included only the interaction between semester and course delivery method in the analysis. The results of this analysis, excluding the problematic data from 2009, are shown in *Tables 3* and *4*.

TABLE 3: Attrition Rate ANOVA by Semester and Course Delivery Method: Goodness of Fit Statistics (Data Excluding 2009)

Observations	210.000
DF	206.000
R²	0. 125
Adjusted R²	0. 113

TABLE 4: Type III Sum of Squares Analysis for Attrition Rate ANOVA by Semester and Course Delivery Method (Data Excluding 2009)

Source	DF	Sum of squares	Mean squares	F	Pr > F
Course delivery method	1	0.488	0.488	25.635	< 0.0001**
Semester	1	0.057	0.057	2.982	0.086
Course delivery method/semester	1	0.015	0.015	0.810	0.369

In *Table 4*, it is apparent that the only significant differences are among courses with different delivery methods (online courses taught in the fall do not have a statistically different retention rate than those taught in the spring in this sample, for example). It may be that this pattern is caused by some other confounding variable (such as previous online course exposure or success) that tends to vary regularly by semester, since it seems implausible that time of year alone would influence online attrition rates. Therefore, rather than continue to explore the relation with attrition by semester, we consider the effects of both previous online exposure and previous online success on future online enrollment and success in our next analyses.

Question 2: *Is previous exposure in online courses a good predictor of future online enrollment and/or success?*

We hypothesize that students who have previously successfully completed[1] an online course are more likely to succeed in a future online course. But it is not apparently obvious what patterns might be seen with students who have previously taken an online course that was not completed successfully. To assess whether or not the number of previous online courses taken has any significant predictive value for determining the likelihood of success in future online courses, a binary logistic regression analysis was run with course success as the dependent variable and the

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[1] Throughout this paper we refer to "success rates" in courses. These are defined as the percentage of students who earned a "C" grade or better as opposed to those students who earned a "D","F","W", or "WU" designation. A "WU" designation at the College is given to students who stop attending classes before the college's official withdrawal deadline but fail to formally withdraw from the class; this deadline occurs the last day of the ninth week of classes each semester. Students who stop attending class after this date receive an "F" grade instead of a "WU" designation. Students who officially withdraw from a course after the third week of classes receive a "W" designation. "ABS" and "INC" designations both indicate an "incomplete" for the course, and are not included in success or attrition rates here.

number of online courses previously taken as the independent variable in order to see if there is any significant predictive relationship between these two measures. *Table 5* shows summary statistics giving the number of students in each category, along with the different success and retention rates for each group of students.

TABLE 5: Summary Statistics of Previous Online Experience with Success and Retention Rates

Number of Previous Online Courses Taken	N	Distribution	Success Rates	Retention Rates
0	698	72.6%	58.2%	68.6%
1	236	24.6%	63.1%	74.6%
2	25	2.6%	52.0%	56.0%
3	2	0.2%	50.0%	50.0%

It seems as though students who have taken at least one online course do better in a subsequent online course than those who have never taken an online course. Interestingly, students who have previously taken multiple online courses have lower success rates than students with no online experience or than those who have taken more than one online course. In order to determine if these differences are statistically significant, we turn to the results of our binary logistic regression analysis. *Table 6* indicates that results of the binary regression analysis are in fact not statistically significant, because the probability is 0.487, well above an alpha level of 0.05. Repeating this analysis for retention rates yields similar results, although they are closer to statistical significance at a probability of 0.136 (See also *Table 6*).

TABLE 6: Type III Analysis (Binary Logisitic Regression for Success/Retention Rates by Number of Previous Online Courses Taken)

Source	DF	Chi-square (Wald)	Pr > Wald	Chi-square (LR)	Pr > LR
Number of Previous Online Courses Taken (analysis using success rates)	3	2.421	0.49	2.436	0.487
Number of Previous Online Courses Taken (analysis using retention rates)	3	5.528	0.137	5.543	0.136

These results lead us to conclude that there is no clear statistically significant relationship between prior online exposure and success in online courses in general; however, we are interested in exploring this relationship in more detail. It may be that specific kinds of prior online exposure increase or decrease the probability of future online success, and a general analysis that looks only at the number of online courses taken and not at the type of prior online experience may be inconsequential because there is too much variation in type of prior online course experience.

Based on the literature, it can be expected that students who successfully completed prior online courses would be more likely to successfully complete future online courses; however, it is unclear whether prior online success or withdrawal might make a student more or less likely to successfully complete an online course than a student who has never taken a course online. Perhaps prior online experience, even if initially unsuccessful, might give students enough familiarity with the online environment and its expectations that they would then be able to use this to succeed in a future course. On the other hand, non-success in a prior online course might negatively impact Internet Self-efficacy, making students more comfortable with dropping or failing an online course a second time due to a lower confidence level in their ability to succeed online. Or, there may simply be features that make some students less likely to be successful online generally, and a prior unsuccessful online experience might be one way of identifying students in this category. In order to determine which effect prior online experience might have,

we began by dividing students into four "prior online experience" groups, named (somewhat artificially) as follows: 1) "successful" or successfully completed all prior online courses taken; 2) "sometimes successful" or successfully completed at least one prior online course; 3) "unsuccessful" or has not successfully completed any prior online courses; and 4) "no online experience" or never taken an online course at the College. A binary logistic regression analysis was then preformed with success rates as the dependent variable and prior online experience as the independent variable. *Table 7* displays the basic distribution of prior online course experience: most students had never taken an online course at the College before, but a reasonably sized minority has taken a prior course either successfully or unsuccessfully (however, only a tiny minority has taken at least one prior online course successfully and at least one unsuccessfully); it also shows the online success and retention rates for each group.

TABLE 7: Prior Online Course Experience Type: Distribution, Success and Retention Rates

Group	*N*	Distribution	Success Rates	Retention Rates
Unsuccessful	89	9.3%	9.0%	39.3%
Sometimes Successful	12	1.2%	41.7%	41.7%
No Online Experience	698	72.6%	58.2%	68.6%
Successful	162	16.9%	92.6%	93.2%

While the success rate for students with no prior online experience of 58.2% is very close to the average success rate for the online courses in the sample (59.2% overall), the success rates for "unsuccessful" online students and "successful" online students differ radically from this average. In order to determine if the differences in these rates for each group are statistically significant, we turn to the results of our regression, which are displayed in *Tables 8, 9 and 10*.

TABLE 8: Goodness of fit statistics (Binary Logistic Regression for Success Rates by Previous Online Course Experience)

Statistic	Full
Observations	961
DF	957
-2 Log(Likelihood)	1104.590
R²(McFadden)	0.150
R²(Cox and Snell)	0.184
R²(Nagelkerke)	0.248

TABLE 9: Type III analysis (Binary Logistic Regression for Success Rates by Previous Online Course Experience)

Source	DF	Chi-square (Wald)	Pr > Wald	Chi-square (LR)	Pr > LR
Previous Online Experience	3	105.751	< 0.0001	194.852	< 0.0001**

**p < .01

TABLE 10: Planned Contrasts for Single Factors(Binary Logistic Regression for Success Rates by Previous Online Course Experience)

Contrast	DF	Chi-square	Pr > Chi²
Unsuccessful vs Sometimes Successful	1	8.152	0.004*
Unsuccessful vs Successful	1	103.071	< 0.0001**
Unsuccessful vs No Online Exp.	1	48.829	< 0.0001**
Sometimes Successful vs Successful	1	18.926	< 0.0001**
Sometimes Successful vs No Online Exp.	1	1.272	0.259
Successful vs No Online Exp.	1	50.298	< 0.0001**

*p<.05 **p < .01 (These p-values represent the total pooled α for all pairwise comparisons in this table; the corresponding p-values for each planned comparison, adjusted using the Bonferroni procedure], are 0.0083 and 0.0017, respectively.)

The Nagelkerke R^2 is 0.248 (See *Table 8*), suggesting that 24.8% of the variance in the chosen model for online course success could roughly be attributed to prior online course experience alone. This is a large effect size. In *Table 9*, the p-value is highly statistically significant ($\alpha=0.01$), at <0.0001, so prior online course experience is a highly significant predictor of future online course success. In particular, *Table 10* shows that the difference between every single pair of groups was highly statistically significant, with the exception of the differences between "sometimes successful" and "no online experience" (and it may be that this difference would actually be statistically significant with a larger "sometimes successful" sample size, which is only 12 students in this sample). It is particularly interesting to note that students in the "sometimes successful" group, who have succeeded in at least one prior online course, but have also had non-success in at least one prior online course, are still significantly less likely to succeed in a future online course than "successful" students: the *p*-value for differences between the "successful" group and "sometimes successful" group is <0.0001, whereas the *p*-value for the differences between the "unsuccessful" group and "sometimes successful" group is 0.004, a difference that is distinct by a factor of at least 40. While the sample size of the "sometimes successful" group is too small to draw any firm conclusions, this does suggest that research with a larger sample size might well reveal that the effect of non-success in a prior online course is even more powerful than the effect of success in a prior online course, since students who have had both seem to have future success rates that may be closer to the students who have only previously experienced online non-success.

This binary logistic regression analysis is repeated for retention rates (as the dependent variable) instead of success rates, to see if results are similar for online retention. These results are shown in *Tables 11, 12* and *13*.

TABLE 11: Goodness of Fit, Binary Logistic Regression for Retention Rates by Previous Online Course Experience.

Statistic	Full
Observations	961
DF	957
-2 Log(Likelihood)	1084.414
R^2(McFadden)	0.080
R^2(Cox and Snell)	0.093
R^2(Nagelkerke)	0.132

TABLE 12: Type III analysis (Binary Logistic Regression for Success Rates by Previous Online Course Experience)

Source	DF	Chi-square (Wald)	Pr > Wald	Chi-square (LR)	Pr > LR
Previous Online Experience	3	69.088	< 0.0001	94.207	< 0.0001**

**p < .01

TABLE 13: Planned Contrasts (Binary Logistic Regression for Success Rates by previous online course experience)

Contrast	DF	Chi-square	Pr > Chi²
Unsuccessful vs Sometimes Successful	1	0.024	0.876
Unsuccessful vs Successful	1	64.451	< 0.0001**
Unsuccessful vs No Online Exp.	1	27.525	< 0.0001**
Sometimes Successful vs Successful	1	19.839	< 0.0001**
Sometimes Successful vs No Online Exp.	1	3.583	0.058
Successful vs No online Exp.	1	32.381	< 0.0001**

**p < .01 (This p-value represents the total pooled α for all pairwise comparisons in this table; the corresponding p-value for each planned comparison, adjusted using the Bonferroni procedure], is 0.0017.)

Here the Nagelkerke R^2 is 0.132 (See *Table 11*), suggesting that 13.2% of the variance in the chosen model for online course retention could roughly be attributed to prior online course experience alone. This is a large-sized effect. *Table 12* shows that again prior online course experience is highly statistically significant, this time for course retention, since again the p-value for the overall model is <0.0001. In *Table 13*, the pairwise comparisons for each type of prior online course experience shows that all the prior online course experience types are highly significantly different from one another, except a few that involve comparisons of students in the "sometimes successful" group (which may simply be not statistically significant because of the small sample size of 12). However, the "sometimes successful" group still has highly statistically different retention rates than the "successful" group.

Implications

For Research

One of the main results of this study is that some prior online non-success seems to lower the chances of future online success, but the reasons for this are not entirely clear. One explanation, supported by the literature, is that having at least one prior unsuccessful online experience has negative impacts on students Internet Self-efficacy. However, future qualitative research is needed to confirm if this is the case or if prior online non-success predicts lower levels of future online success because these students have other specific traits that make them less likely to succeed online.

The groups of students who succeeded in some prior online courses but not in others is a particularly interesting group that this study could not focus on in much detail because they made up such a small proportion of the sample. This group was still highly significantly less likely to succeed in a future online course than students who had succeeded in all prior online courses (*p*-value<0.0001), although they were highly statistically significantly more likely to succeed than students who had taken prior online courses without ever successfully completing them (*p*-value=0.004). While the sample size of the "sometimes successful" group is too small to draw any firm conclusions beyond this statistical significance, this does suggest that research with a larger sample size might well reveal that the effect of non-success in a prior online course is even

more powerful than the effect of success in a prior online course, since students who have had both seem to have future success rates that may be closer to the students who have only previously experienced online non-success. Further research on this group with a larger sample size is an obvious next step.

For Practice

Because success and retention rates in this study had such a distinct relationship to prior online course success, our results seem to suggest that as soon as a student has at least one successful online course experience, barriers to learning decrease (either because they are overcome in the initial experience or student perceptions are more in line with the actuality of online learning); this substantiates previous findings by Muilenburg & Berge (2005). Our findings also suggests that community college support services for online courses could be most effectively targeted at those students who have previously withdrawn from or earned a "D" grade or below in an online course, as these are the students at highest risk of dropping out or failing a future online course. Ludwig-Hardman & Dunlap (2003) state there is a great need for individualization in learner support services for online courses, such as providing guidance, counseling, assessment and coaching. To this end, e-advisors could pre-identify students, based on previous online experience, who potentially will need individual assistance and reach out to them at the beginning of the semester to begin a one-on-one advising process. Such an intervention could include diagnostic procedures, such as intake interviews and self-assessment tools, to assist students in evaluating their preparedness for re-enrolling in online courses and to identify specific areas of improvement in which e-advisors could offer individualized support.

In addition, unsuccessful students have been found to need more course management assistance to learn the course layout and understand expectations and assignments (Morris & Finnegan, 2008-9). Combined with our findings, this suggests that e-advisors need to be well-versed in helping students navigate the course structure in order to potentially impact Internet self-efficacy. Moreover, greater attention may be needed by instructors on instructional design issues, such as following basic rules of good Web design, providing clear instructions, using consistent language and providing a comprehensive course orientation at the beginning of the

semester, in order to increase previously unsuccessful students' sense of confidence and success in the online environment (Hachey, 2005; Morris & Finnegan, 2008-9).

Finally, targeted support could also be aimed at students with no prior online course experience, although our results suggest that these students may need less intensive support than those students who have had at least one prior experience of non-success online. Fear of the unknown may be critical for novice online learners and improving social interaction at the beginning of the semester can help to mitigate this issue (Muilenburg & Berge, 2005). One potential solution may be to encourage online introductions and sharing of information at the beginning of the semester in order to build a sense of community within the online environment, as a "sense of belonging" has been noted as critical for retention (Tinto, 1975). Another way to encourage social interaction could be to establish peer mentoring, pairing experienced successful online students (who our findings suggest are likely to do better online) with students new to the online environment (who are likely more at-risk).

Limitations

This study consisted of a sample of one higher learning institution among many. Therefore, characteristics of this particular community college may limit the applicability of these findings to other institutions. This limitation may be off-set to some degree in that the community college in this study represents a diverse student body that mirrors many community colleges in the United States. Additionally, its size is noteworthy. Large institutions, those with greater than 15,000 total enrollments such as the one in this study, constitute 14% of all institutions with online offerings, but educate nearly two-thirds (64%) of all online students (Allen & Seaman, 2010). In addition, studying students at a single institution, as opposed to across institutions, controls for several threats to internal validity, such that students are more likely to have been exposed to similar conditions regarding course requirements, faculty and institutional elements (Nora & Cabrera, 1996).

In addition, while the total size of this sample was relatively large, the number of students in each subcategory was not always particularly large, and in some cases was actually quite small. For example, the number of students who had both successfully and unsuccessfully completed

some online courses in the past was very small, and the number of students, who previously took an online course, while a reasonable size, could have yielded more statistical power had it been larger. While the sample sizes in this study were large enough to yield several significant findings, the research might have gone further with a larger sample size. This suggests that additional research with larger sample sizes could prove fruitful.

Another limitation of this study is that although it captures important issues that affect retention, it does not capture all of them. There are many other factors that affect student retention and which were not included here. Specifically, social integration (a student's ability to integrate their education with other aspects of their lives such as work, family, friends, etc. (Kember, 1995), was not addressed in this work. The quantitative analysis conducted in this study is likely not accounting for personal issues that may be important when considering student withdrawal. In particular, it may be that higher attrition online is a result of the type of students who take online courses in the first place: the students who enroll online may be doing so due to higher personal demands (Dobbs, Waid & del Carmen, 2009), which negatively impacts their ability to socially integrate their lives with their education. This suggests the need for additional qualitative research to capture a fuller view of online persistence.

Conclusions

This study clearly shows that prior online course experience is strongly correlated with future online course success. In fact, knowing a student's prior online course success explains 13.2% of the variation in retention and 24.8% of the variation in online success in our sample, a large effect size. Students who have not successfully completed any previous online courses have very low success and retention rates, and students who have successfully completed all prior online courses have fairly high success and retention rates. Students who have had some online success and some online non-success in the past have distinctly lower success rates than those students whose prior online experiences have all been successful, but the sample size in this study was not large enough to draw further conclusions about this group. Therefore, this study suggests that additional support services need to be provided to previously unsuccessful online

learners, while students who succeed online should be encouraged to enroll in additional online courses in order to increase retention and success rates in online learning.

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