41st NEAIR Conference Program

Life, Liberty and the Pursuit of IR

The Code of IR Ethics and Professional Practice

November 8 – 11, 2014

Hyatt Regency Philadelphia at Penn's Landing
Philadelphia, Pennsylvania

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NEAIR
North East Association for Institutional Research
A guiding light for your institutional research community

Dear friends and colleagues,

The 41st North East Association for Institutional Research annual conference was held November 8-11, 2014 at the Hyatt Regency Philadelphia at Penn's Landing in historic Philadelphia, Pennsylvania. Our conference theme of ***Life, Liberty, and the Pursuit of IR*** was built up from this historic Philadelphia location to underscore our moral obligation to serve and to help foster informed judgments on policy and decisions that affect our personal and collective liberties, and prosperity. ***Life, Liberty, and the Pursuit of IR*** encapsulates the belief that how we perform and how well we do it, and the differences we as institutional researchers make affect the promise of a better life for each progressive generation of students within our colleges and universities, and of our society at-large.

These *Proceedings* document the unparalleled spirit of the NEAIR community in which best practices in institutional research, assessment, strategic planning, data management, survey research, and all the other areas that IR professionals specialize in are shared freely and openly. We are indeed a unique breed, and these *Proceedings* showcase the best that we do, and did, as captured at the 2014 NEAIR annual conference.

With 478 attendees in total, the meeting space in the Hyatt at Penn's Landing needed to be masterfully managed by our Conference Planning team, led by Annemarie Bartlett, Program Chair, Leon Hill, Local Arrangements Chair, and Beth Simpson, NEAIR Administrative Coordinator – and it was. In addition to the total number of attendees setting yet another NEAIR attendance record, we also set the record for the number of members in attendance, at 436. Our strongest showing yet by Exhibitors, coupled with invited speakers and a few visiting colleagues and friends from years past comprised the difference between the member and total attendance figures.

I am pleased to report that attendee satisfaction with networking and professional development was again among the highest rated areas in the conference evaluation, along with program content – a testament to the great sharing of knowledge and camaraderie among NEAIR members.

With special thanks to Tiffany Parker, our Publications Chair, please do enjoy this record of the 41st NEAIR annual conference.

Bruce Szelest
NEAIR President 2013-14

ACKNOWLEDGEMENT

Contained in these pages are the Proceedings of the NEAIR 41st Annual Conference provide eight contributed conference papers/presentations authored by 12 NEAIR colleagues.

Additional conference presentations are just a few clicks away – accessible within in the NEAIR website under the Annual Proceedings section. These pages are only accessible to signed in NEAIR members.

Special thanks to Bruce Szelest, Annemarie Bartlett, Jennifer May and Beth Simpson for their contributions, oversight, and support with all aspects of publications responsibilities during the course of this past year.

Tiffany Parker

2014-2015 NEAIR Publications Chair

Mt. Wachusett Community College

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** Indicates Best Paper Award

Community College Transfer Students' Persistence at University

Paper Submitted to NEAIR November 2014

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Denise Nadasen

University of Maryland University College

Of the 7.7 million students enrolled in community college in the U.S., 81% indicate a desire to earn a four-year credential (Alstadt, Schmidt, & Couturier, 2014). Yet, only 20% of community college students transfer to a four-year institution within five years (Alstadt et al., 2014). According to data from the National Student Clearinghouse, only 15% of community college students earn a four-year degree six years following transfer (Shapiro et al., 2012).

Much of the research on community college transfer students at four-year institutions has focused on issues of academic preparedness and transfer student performance, in comparison to that of native students (e.g., Diaz, 2006; Glass & Harrington, 2010). The research literature has been more limited in examining students' *persistence* or continued progress toward reaching their goal of earning a four-year degree.

There are a number of reasons why community college students may have difficulty in persisting to graduation. For one, 60% of community college students are enrolled part-time (Community College Research Center, 2014). Part time enrollment results in students taking more time to reach their academic goals and may indicate that students have other competing priorities, including family and work commitments, that may impede their academic progress. Indeed, community college students are disproportionately more likely to be low income, minority, and first-generation students (Berkner & Choy, 2008) and therefore more likely to experience financial constraints that impede persistence (Cabrera, Nora, & Castaneda, 1992).

Further, Bailey, Jeong, and Cho (2008) suggest that community college students may experience challenges in persistence due to their need to complete developmental education courses prior to earning college level credit.

The challenges students experience in persistence at the community college, further, carry-over to difficulties in persistence at the four-year level. The literature has identified the transition from community college to a four-year institution as particularly stressful for students, needing to adjust to a new academic climate, demanding greater independence (Townsend & Wilson, 2006). Further, students may need additional preparation to meet the demands of a four-year university (Glass & Harrington, 2010; Townsend, 1995). Beyond the focus on academic readiness, more research is needed to understand factors associated with transfer student persistence at a four-year institution.

In understanding factors associated with students' persistence, we can look to theoretical models of student attrition. Specifically, Tinto and Cullen (1973) introduced a model of student withdrawal, focused on factors predictive of students' intent to drop out. Tinto and Cullen (1973) identified a number of individual psychological factors associated with students' decisions to drop out including learners' *goal commitment* to obtaining a credential and *institutional commitment* to a particular college or university. These two components of psychological commitment are based on students' experiences of *academic integration*, including their academic performance and intellectual development, and on *social integration*, arising from students' interactions with peers and faculty (Tinto, 1975; Tinto & Cullen, 1973). Since Tinto's introduction of this seminal model much work has been done to validate the association between the psychological constructs proposed and student attrition (e.g., Berger & Braxton, 1998; Braxton, Sullivan, & Johnson, 1997) as well as to understand how institutions can better foster students' academic and social integration (Berger & Milem, 1999; Braxton & McClendon, 2001; Tinto, 1997).

At the same time, this model has been critiqued for its focus on traditional college students at residential institutions. Specifically, Bean and Metzner (1985) suggest that Tinto's model may not address the experiences of older, part-time, and non-residential or commuter students. These non-traditional learners are more prevalent among community college transfer students. Bean and Metzner suggest that while in Tinto's model of attrition, students decisions to drop out are driven by a lack of socialization and integration into the institution, such inter-personal concerns may be less pertinent to non-traditional students who have well-developed social lives outside of institutions. Indeed, Pascarella and Chapman (1983) in examining Tinto's model of student attrition across two-year and four-year institutions, found that while social integration was key to students' withdrawal decisions at four-year institutions, it had a more limited effect in two-year and four-year non-residential institutions. Social integration may be even less important for community college transfer students, who are non-residential and transition across institutions.

Additionally, Bean and Metzner (1985) suggest that attrition for non-traditional learners may be more affected by factors in the external environment including students' finances and family and job responsibilities. Family and employer support of the students' academic efforts play a major role in determining the persistence of non-traditional students as does learners' perceptions of the relevance of course work to their lives (Park & Choi, 2009).

In addition to external factors impacting community college students' persistence *during* their studies at a four-year university, a variety of factors existing prior to students' enrollment at an institution may influence their persistence. Tinto and Cullen (1973) conceptualize these as including students'' *individual attributes, family background*, and *pre-college schooling*. In Bean and Metzner's model these are specified as gender, age, ethnicity, as well as high school performance. For transfer students, this list of external factors may need to be expanded to included students' academic experiences at the community college. In fact, students' initial post-secondary academic experiences at a two-year institution may be particularly important in setting the stage for their persistence at the four-year level. While demographic factors (e.g., gender, race/ethnicity) contributing to students' persistence at university have been widely examined (e.g., Peltier, Laden, &Matranga, 1999; Tross, Harper, Osher, & Knwidinger, 2000; Wang, 2008), students' academic backgrounds prior to enrollment at a four-year institution have received limited attention. Given the emphasis placed on community college transfer students' academic preparedness for four-year course work (Carlan & Byxbe, 2000; Diaz, 2006; Townsend, 1995), more work is needed to examine the relationship between transfer students' academic backgrounds and university persistence (Murtaugh, Burns & Schuster, 1999).

In addition to critiques that models of persistence (e.g., Tinto, 1975) fail to address non-traditional students and that empirical work has not fully examined students' academic experiences, particularly across institutions, models have been critiqued for focusing on limited indicators of persistence. Pascarella, Smart, and Ethington (1986) point out that studies of persistence focus on limited periods of time and rarely track students' progress beyond the one- or two-year point. Examining persistence over more extended periods of time may be particularly important for non-traditional students who are more likely to be enrolled part time, therefore requiring more time to earn a credential, and more likely to stop-out occasionally for external reasons.

In this study, we intended to address at least three imitations in prior research. First, in examining persistence, we focus on a sample of non-traditional students, those transferring from community college to a four-year university. Second, in predicting transfer students' persistence at a four-year institution, both demographic factors and factors associated with students' academic backgrounds across institutions are explored. In particular, students' course taking behaviors and performance at the community college and their performance in the first semester of transfer at a four-year institution were examined. A dearth of this type of cross-institutional analysis of students' academic backgrounds is a key limitation in the research on community college transfer students (Pascarella et al., 1986). Third, rather than examining a single indicator of persistence, three separate persistence metrics are examined: (a) students' *re-enrollment* (i.e., enrollment in the immediate next-semester, following the first semester of transfer), (b) *retention* (i.e., re-enrollment within a 12-month window, following the first semester of transfer), and (c) *graduation* (i.e., earning a first bachelor's degree). Using these indicators allowed us to examine both students initial persistence at the transfer institution (i.e., re-enrollment) and follow progress through an eight-year period (i.e., graduation).

Finally, community college transfer students' persistence was examined at an online, four-year institution. The rise of online learning has particularly attracted a greater number of non-traditional students to post-secondary education. Yet, limited work has examined students' persistence in online learning (Berge & Huang, 2005). As with non-traditional students more generally, social integration may play a less prominent role in persistence in online learning, where students may have more limited face-to-face content with peers and faculty (Boston, Diaz, Gibson, Ice, Richardson, & Swan, 2009). As a result, external factors, including students' demographic and community college backgrounds, may be all the more important to understanding persistence at an online university.

To address these issues, the following research questions were investigated:

1. To what extent do demographic factors, community college academic factors, and factors associated with first-term performance at the transfer institution predict transfer student re-enrollment at a four-year, online university?
2. To what extent do demographic factors, community college academic factors, and factors associated with first-term performance at the transfer institution predict transfer student retention at a four-year, online university?
3. To what extent do demographic factors, community college academic factors, and factors associated with first-term performance at the transfer institution predict transfer students' eight-year graduation from a four-year, online university?

Methods

Participants

Participants in this study included 8,058 community college transfer students, whose first semester of transfer at the four-year, online institution was between Spring 2005 to Spring 2011. Only students pursuing a first bachelor's degree were included in the analyses. The sample was on average 29 years old (*SD*=8.4) and majority female (57.6%, n=4638; male: 41.2%, n=3323). The sample was racially and ethnically diverse: 24% White (n=1956), 44% African American (n=3509), 10% Asian (n=839), 10% Hispanic/Latino (n=821), and 1% American Indian (n=75). Further, 14% of students did not specify a race or ethnicity. The full student sample was used in predicting re-enrollment and retention.

To predict graduation, a subset of this sample was used (n=2040). These were students who transferred to the four-year institution between Spring 2005 and Spring 2006. Only those students who had had eight years to complete a degree were selected for inclusion in this sample.

Data Collection

Data were assembled through a data sharing partnership between a four-year university and two community colleges. Data were collected on students' demographics (i.e., age, gender, race/ethnicity, marital status) and first-term performance at the transfer institution (i.e. first-term GPA, first-term credits earned) from the four-year institution's students information system. Further, students' community college course taking behavior (i.e., math, and English enrollment, developmental education enrollment) and performance records (i.e., successful course completion, community college GPA, credits earned, AA degree earned) were attained from the community colleges and matched to students' records at the four-year institution.

Results and Discussion

Descriptive data of persistence indicators for the sample are presented in Table 1.

Table 1
Descriptives of student persistence

Persistence Indicator	Population Performance
Re-enrollment	**67%** (n=5376)
Retention	**79%** (n=5376)
Eight-Year Graduation	**49%** (n=498)

Logistic regression was used to predict each of the target measures of persistence (i.e., re-enrollment, retention, and eight-year graduation). Each persistence factor was dichotomously coded (i.e., re-enrolled or not; graduating within an eight-year period or not).

Predicting Re-enrollment

The overall model predicting re-enrollment was significant, $X^2(19) = 1063.24$, $p<.001$. The model was able to correctly classify 71.6% of students as re-enrolling or not. Pseudo R^2

measures of effect size ranged from an estimated 12.5% of variance in re-enrollment explained (Cox & Snell's R^2) to 17.4% of variance (Nagelkerke's R^2) explained. Table 2 presents demographic, community college, and first-term indicators predictive of re-enrollment.

Table 2

Predicting re-enrollment using demographic characteristics, community college course taking behaviors, summative measures of CC backgrounds, and university first-term indicators

<table>
<tr><th colspan="2"></th><th>β</th><th>SE(β)</th><th>Significance</th><th>β*</th></tr>
<tr><td colspan="6">Demographic Characteristics</td></tr>
<tr><td colspan="2">Gender***</td><td>0.20</td><td>0.05</td><td>0.000</td><td>1.22</td></tr>
<tr><td colspan="2">Age</td><td>0.00</td><td>0.00</td><td>0.638</td><td>1.00</td></tr>
<tr><td rowspan="5">Race/ Ethnicity:</td><td>Black*</td><td>0.17</td><td>0.07</td><td>0.013</td><td>1.19</td></tr>
<tr><td>Hispanic/Latino</td><td>-0.02</td><td>0.10</td><td>0.83</td><td>0.98</td></tr>
<tr><td>Asian</td><td>0.07</td><td>0.10</td><td>0.492</td><td>1.07</td></tr>
<tr><td>American Indian</td><td>0.19</td><td>0.27</td><td>0.469</td><td>1.21</td></tr>
<tr><td>Race Not Specified</td><td>0.05</td><td>0.09</td><td>0.60</td><td>1.05</td></tr>
<tr><td colspan="2">Marital Status**</td><td>0.24</td><td>0.07</td><td>0.001</td><td>1.28</td></tr>
<tr><td colspan="2">PELL Grant Recipient</td><td>0.13</td><td>0.07</td><td>0.065</td><td>1.14</td></tr>
<tr><td colspan="6">Community College Course Taking</td></tr>
<tr><td colspan="2">Repeated a Course**</td><td>0.17</td><td>0.06</td><td>0.005</td><td>1.19</td></tr>
<tr><td colspan="2">Enrolled in a Developmental Course***</td><td>0.21</td><td>0.06</td><td>0.001</td><td>1.23</td></tr>
<tr><td colspan="2">Exempt from Developmental Math**</td><td>0.22</td><td>0.08</td><td>0.004</td><td>1.25</td></tr>
<tr><td colspan="6">Summative Measures of Community College Backgrounds</td></tr>
<tr><td colspan="2">Community College GPA**</td><td>-0.11</td><td>0.04</td><td>0.005</td><td>0.89</td></tr>
<tr><td colspan="2">Cumulative Credits Earned at CC</td><td>-0.00</td><td>0.00</td><td>0.208</td><td>1.00</td></tr>
<tr><td colspan="2">Earned an Associate's Degree</td><td>-0.13</td><td>0.07</td><td>0.059</td><td>0.88</td></tr>
<tr><td colspan="6">First Term at University</td></tr>
<tr><td colspan="2">First Term GPA***</td><td>0.26</td><td>0.02</td><td>0.000</td><td>1.30</td></tr>
<tr><td colspan="2">First Term Credits Earned***</td><td>0.14</td><td>0.01</td><td>0.000</td><td>1.14</td></tr>
<tr><td colspan="2">Enrolled Full Time</td><td>-0.16</td><td>0.08</td><td>0.054</td><td>0.86</td></tr>
<tr><td colspan="2">Cumulative Credits Transferred***</td><td>0.01</td><td>0.00</td><td>0.000</td><td>1.01</td></tr>
</table>

Note: *sig. at 0.05 level, ** sig. at 0.01 level, *** sig, at 0.001 level

Examining demographic characteristics, determined that gender and marital status were both significant predictors in the model. Specifically, being female and married increased students' probability of re-enrolling in a subsequent term at the four-year university. Further,

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race/ethnicity designated as African American was a significant positive predictors of re-enrollment.

In examining community college course taking behaviors, students' likelihood of re-enrollment increased if they either enrolled in a developmental course or were exempt from developmental math. Further, repeating a course at the community college was found to be a significant, positive predictor of re-enrollment; in other words, re-taking a course in community college increased the likelihood that students' would re-enroll. While this finding may appear to be counter-intuitive, it may reflect the fact that students willing to retake courses may be more tenacious in working toward their goals, despite challenges they may experience.

Summative measures of students' community college academic experiences found only community college GPA to be a significant predictor in the model. Further, community college GPA was a negative predictor of re-enrollment. More work is needed to understand why this may be the case. One possibility is that those students earning a high GPA at the community college may be more sensitive to "transfer shock" (Townsend, 1995). These students' GPAs may experience a more dramatic dip at the four-year institution requiring a greater adjustment to a new learning environment. Alternately, students academically success at the community college, may determine that they prefer face-to-face courses, and, after a semester at the online transfer institution, may elect to transfer to a more traditional university.

Looking at first-term of transfer indicators, as may be expected, first term GPA and total number of credits earned were significant predictors of re-enrollment. Further, the cumulative number of credits transferred from community college was a significant positive predictor in the model. Number of credits transferred may reflect the pragmatic value of community college course work in helping students meet four-year academic requirements. Examining standardized beta coefficients in the model revealed first-term GPA to be the strongest predictor of re-enrollment at the four-year institution..

Predicting Retention

The model predicting student retention was significant overall, $X^2(17) = 1271.59$. The model correctly classified 80.5% of cases as retained or not. Effect size measures suggest that between 14.8%, according to Cox and Snell's R^2, and 23.1%, according to Nagelkerke's R^2, of variance in retention was explained by the model.

Table 3 presents demographic, community college, and first-term indicators predictive of retention. As with re-enrollment, a number of demographic characteristics proved to be significant. Married females were more likely to persist, as were African American students and those having an unspecified race/ethnicity.

Examining students' community college course-taking behavior determined that repeating a course and being exempt from or completing developmental math were positive predictors in the model. In considering summative measures of community college performance, cumulative GPA at the community college was found to be a negative predictor in the model, as it was in the model predicting re-enrollment. As a contrast, first term GPA at the transfer institution was a significant and positive predictor of retention. The total number of credits attempted in the first term, the dichotomized variables part-time or full time status, and the number of credits transferred from the community college were all found to be significant positive predictors of retention.

A number of additional factors were considered as potentially predictive of retention. These included, receiving an Associate's degree at the community college, credits earned and attempted at the community college, and average community college course load. However, all of these factors were non-significant predictors and were removed from the final model for greater parsimony. In particular, community college course taking behaviors were not significantly predictive of retention; these included enrollment in Math, English, Computers, or Speech courses as well as enrollment in Honors, Developmental, and Online courses. Successful course completion indices were also not found to be significantly associated with retention at the transfer institution.

Table 3
Predicting retention using demographic characteristics, community college course taking behaviors, summative measures of CC backgrounds, and university first-term indicators

	β	**SE(β)**	**Significance**	**β***
Demographic Characteristics				
Gender* **	**.180**	**.063**	**.004**	**1.197**
Age at Transfer	-.005	.004	.170	.995
Race/ Ethnicity: Compared: **Black****	**.231**	**.081**	**.005**	**1.259**
Hispanic/Latino	.027	.113	.810	1.028
Asian	.017	.115	.883	1.017
American Indian	-.206	.291	.480	.814
Race Not Specified*	**.048**	**.104**	**.648**	**1.049**
Marital Status**	**.246**	**.090**	**.006**	**1.279**
PELL Grant Recipient	.148	.084	.079	1.159
Community College Course Taking				
Repeated a Course**	**.223**	**.065**	**.001**	**1.249**
Completed Developmental Math*	**.174**	**.084**	**.037**	**1.191**
Exempt from Developmental Math	.075	.089	.399	1.078
Summative Measures of Community College Backgrounds				
Community College GPA**	**-.127**	**.043**	**.003**	**.881**
First Term at University				
First Term GPA***	**.590**	**.022**	**.000**	**1.803**
First Term Credits Attempted***	**.160**	**.013**	**.000**	**1.174**
Enrolled Full Time***	**-.716**	**.131**	**.000**	**.489**
Credits Transferred First Term***	**.013**	**.001**	**.000**	**1.013**

Note: *sig. at 0.05 level, ** sig. at 0.01 level, *** sig, at 0.001 level

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Predicting Graduation

The model predicting graduation was significant overall, $X^2(17) = 1271.59$; correctly classifying 69.6% of cases as retained or not. Effect size measures indicated that between 20.0%, according to Cox and Snell's R^2, and 26.7%, according to Nagelkerke's R^2, of variance in graduation was explained by the model. Table 4 presents demographic, community college predictors, and first-term indicators predictive of graduation.

Table 4
Predicting graduation using demographic characteristics, community college course taking behaviors, summative measures of CC backgrounds, and university first-term indicators

	β	**SE(β)**	**Significance**	**β***
Demographic Characteristics				
Gender	.029	.106	.785	1.029
First_Term_Age* **	**-.023**	**.007**	**.000**	**.977**
Minority Status	-.169	.104	.104	.845
Receiving PELL at CC	-.262	.167	.116	.770
Community College Course Taking				
Math Enrollment at CC*	**.329**	**.135**	**.015**	**1.390**
Percent Ws at CC	-.670	.381	.079	.512
Summative Community College Measures				
Receiving AA at CC	.127	.129	.325	1.135
CC CUM GPA*	**.168**	**.081**	**.038**	**1.184**
CC Credits Earned	.005	.003	.059	1.005
University First Term Indicators				
First Term GPA* **	**.482**	**.044**	**.000**	**1.619**
First Term Credits Earned* **	**.021**	**.002**	**.000**	**1.022**

Note: *sig. at 0.05 level, ** sig. at 0.01 level, *** sig, at 0.001 level

Among demographic characteristics, only first term age when transferring to the four-year university was found to be a significant predictor. Further, first term age was found to have a negative relation to graduation, such that being younger increased students' likelihood of graduating within an eight-year time period.

Examining coursework at the community college, math enrollment was a significant predictor of graduation. Although other math-related indices, including completing developmental math and the rate of successful math course completion were examined as possible predictors, the dichotomized variable reflecting only whether or not students enrolled in a math course proved to be a sufficient indicator predicting graduation. In terms of summative community college performance indicators, cumulative GPA was a significant positive predictor.

Variables reflecting students' first semester at the transfer institution were all significant, positive predictors. This included factors associated with both performance (i.e., first-term GPA) and course load (i.e., credits earned). In examining standardized beta coefficients, first-term GPA was the strongest predictor of eight-year graduation followed by students having taken a math course at the community college. Taking a math course could be interpreted as a variable indicative of students' academic preparation or of students' willingness to complete requirements necessary for ultimate graduation.

Conclusion

The goal of the present study was to examine three separate indicators of community college transfer persistence: re-enrollment, retention, and eight-year graduation at a four-year, online, university. In particular, we were interested in using demographic, community college, and first-term at transfer institution factors to predict these measures of persistence. Across models, first-term factors at the transfer institution continued to be key indicators of persistence. Even in predicting graduation eight years after the first semester of transfer, students' first term factors (i.e., first-term GPA and first-term credits earned) were significant predictors. This is consistence with prior research that has emphasized the first semester of transfer as a critical point in students' academic careers (Townsend, 2006). In particular, students' volume of course taking in the first semester (e.g., first term credits earned, full time enrollment) were associated with persistence. Academic load may be a particularly important factor for non-traditional students, who may face a variety of challenges in persisting consistently toward their academic goals. Students' abilities to take more credits or to be enrolled full time in the first semester may be indicators of a more general ability to balance academic commitment with external obligations. More work is needed to determine the extent to which community college students maintain consistent levels of enrollment throughout their time at a four-year institution.

While re-enrollment, retention, and eight-year graduation were all able to be successfully modeled, each of these persistence indicators was predicted by slightly varied factors. For instance, while African American status was a significant positive predictor of both re-enrollment and retention, it was not a significant predictor of graduation. Although minority status has typically been considered to be an *at risk* factor for success (Greene, Marti, McClenney, 2008), these students may particularly benefit from the flexibility offered by an online institution, at least in their initial semesters of study.

Across the models, community college background factors were predictive of persistence at the four-year institution. In particular, variables associated with math course-taking at the community college (e.g., completing developmental math, math enrollment at the community college) were associated with persistence. Math course taking may indicate that students have greater academic preparation. It may also be the case that students taking math are more thoughtful about their academic pathways and readily elect to take courses that are required for earning a credential. The importance of community college background factors in predicting persistence suggests the importance of further developing data sharing partnerships between community colleges and four-year institutions.

Future Directions

While the present work is focused on the bookends of students' university experience, specifically students' re-enrollment after their first semester of transfer and ultimate graduation, more work is needed to examine the continuity of non-traditional students' pathways through a four-year institution. Additionally, given the documented role of demographic factors in persistence, examining divergent persistence pathways for students in different demographic categories may hold merit. Likewise, it may be the case that students pursuing various fields of study at the transfer institution may have divergent enrollment trajectories. Finally, in these analyses, students' decisions to persist were considered independent of institutional intervention. However, to the extent that faculty and administrators may take steps to improve student retention and graduation, more work is needed to evaluate the efficacy of various institutional interventions in promoting persistence.

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Final course grades: comparing full and part-time faculty

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Abstract: The percentage of full-time faculty in higher education is declining, and an increasing proportion of students are being taught by part-time instructors. Is there a difference between these two groups of instructors in student final course grades? Knowing the relative effectiveness of different instructor categories could help in promoting better student outcomes through more appropriate resource allocation. When we compare the final course grades of students taught by full and part-time instructors in a career oriented college, our initial evaluation indicates that there is not a significant effect on final course grades due to instructor status. Student characteristics are more relevant to final course grades, a trend which strengthens as students move up in course level from first to fourth year.

Proponents of full-time instructors often claim that part-time instructors result in lower educational outcomes for college students. Yet due to rising cost pressures and accountability expectations, colleges increasingly rely on part-time/adjunct instructors rather than full-time/tenured faculty. Nationally, between 1975 and 2009 the proportion of tenured and tenure-track faculty members shrank from 45 percent to less than 25 percent. Contingent appointments (full and part-time appointments off the tenure track) now make up more than 75 percent of the total instructional staff, and the most rapid growth has been among part-time faculty members, whose numbers increased more than 280 percent from 1975 to 2009 (AAUP, 2011).

But are there differences in student grades associated with part-time and full-time instructors? The research is spotty and mixed: in addition to student characteristics, there is the issue of delivery modalities, since classes can be taught on-ground, on-line, or hybrid. Does any effect vary by subject matter, department, and/or by institutional type and characteristics? Given the complexity, there is limited research, and it is not clear whether full-time and part-time faculty perform differently in terms of student grades. Bettinger and Long (2010) found that part-time instructors seem to have a small positive effect on grades, but primarily in fields related to specific occupational preparation. Figlio, Schapiro, and Soter (2013) discovered that students learn more, across many subject areas, from non-tenure line professors in introductory courses. Johnson (2011) found no differences in student retention between tenured and contingent instructors, but significant differences in grades, with contingent instructors giving higher grades.

Numerous theories exist on why grades might differ between full and part-time instructors: part-time faculty will give higher grades, leading to grade inflation, because their employment renewal depends on student course ratings and hence grading leniency; part-time instructors, since they do not have service requirements, will be better teachers and give higher grades; full-time (tenured) faculty are more rigorous, and will give lower grades; full-time faculty have greater content knowledge, and are better teachers, resulting in higher student grades. In addition, there is the underlying ambiguity of the grading system--what does a grade mean? Does a grade represent a distributional pattern, or is it a reflection of a criterion based approach? Instructors vary in their definition of what a grade means and how it should be awarded.

Data Sources: Goodwin College is a private, non-residential, career-focused institution awarding Associate and Baccalaureate degrees and collegiate certificates. Most Goodwin students are non-traditional, with an average age of 30. The student population is 80% female and 48% students of color. Many of the students are returning to college, working, and/or single parents, so they often have substantial responsibilities outside of the classroom.

The data for this study come from the college's student information system. Final course grade data from the fall of 2013 and the spring of 2014 were used. Students' final grades, on a standard 4.0 scale, and student baseline characteristics, cumulative GPA's, and instructor characteristics are all available from the student information system. Goodwin's academic calendar encompasses three full semesters each year-- fall, spring and summer, so full-time faculty teach 15 courses per year, prior to any release time for other duties.

Typical semester enrollments are around 3,600 students, with an approximate full-time equivalency of 1,650. Course registrations are split 60/40 between part-time and full-time instructors, respectively. Actual course registrations are over 10,000 each semester. After removing ungraded students (withdrawals, Pass/Fail, non-credit remedial courses, etc.), the final data-set had 14,071 course registrations (see Table 1). There were 7,117 course registrations in the fall semester, and 6,954 in the spring, representing 3,258 unique individuals in the fall, 3,170 unique individuals in the spring, and 4,058 total individuals who took a course in either semester.

Table 1 *Graded course registrations by semester and faculty status*

Semester/Faculty Status	Part-time	Full-time	Total
Fall 2013	4,527 (64%)	2,590 (36%)	7,117
Spring 2014	4,096 (59%)	2,858 (41%)	6,954
Total	8,623	5,448	14,071

Goodwin faculty are primarily part-time, as indicated by the Table 2. Goodwin only recently began awarding bachelor's degrees, and still has the student and faculty profiles of a two-year college. The percentage of course enrollments taught by part-time faculty, and overall percentage of part-time faculty teaching, decreases as course levels increase, with upper-level courses (300, 400) being taught primarily by full-time faculty. This has important implications: the lower level your course, the more likely you are to be taught by a part-time instructor.

Table 2a *Instructional Assignments by course level and faculty status*

Course Level/Faculty Status	PT	%	FT	%	Total
ALL	233	77%	70	23%	303
100	174	75%	57	25%	231
200	73	69%	33	31%	106
300	26	55%	21	45%	47
400	2	15%	11	85%	13

Table 2b *Registrations by Course Level and Faculty Status*

Registrations/Faculty Status	PT	%	FT	%	Total
ALL	8,623	61%	5,448	39%	14,071
100	5,861	64%	3,332	36%	9,193
200	1,988	59%	1,364	41%	3,352
300	712	54%	603	46%	1,315
400	62	29%	149	71%	211

Table 3 shows how full and part-time instructors differ in terms of their own characteristics and the characteristics of their students. In summary, full-time faculty teach more upper level courses, and upper level courses have "better" students.

Table 3 *Comparison of full and part-time instructor characteristics*

<table>
<tr><th>Characteristic</th><th>PT</th><th>FT</th><th></th><th rowspan="2">Mean Diff</th><th></th><th></th></tr>
<tr><td></td><td>Mean</td><td>Mean</td><td>Sig.</td><td></td><td></td></tr>
<tr><td>Instructor years of service</td><td>3.32</td><td>5.00</td><td>.000</td><td>-1.68</td><td colspan="2" rowspan="7">These are the characteristics on which PT and FT instructors <u>DO</u> differ. In summary, FT</td></tr>
<tr><td>InsDegDoc</td><td>.26</td><td>.41</td><td>.000</td><td>-.15</td></tr>
<tr><td>TotalEarnedCredits</td><td>42.16</td><td>50.30</td><td>.000</td><td>-8.14</td></tr>
<tr><td>GPA</td><td>2.37</td><td>2.68</td><td>.000</td><td>-.31</td></tr>
<tr><td>Course level</td><td>1.42</td><td>1.55</td><td>.000</td><td>-.14</td></tr>
<tr><td>InsDegMas</td><td>.64</td><td>.56</td><td>.000</td><td>.08</td></tr>
<tr><td>InsDegUnk</td><td>.64</td><td>.56</td><td>.000</td><td>.08</td></tr>
</table>

Characteristic	**PT**	**FT**		Mean		
InsDegBach	.07	.03	.000	.04	faculty teach more upper level courses, and upper level courses have "better" students.	
InsDegCert	.01	.00	.000	.01		
Fall or spring Semester	1.48	1.52	.000	-.05		
Pell recipient	.55	.51	.000	.04		
OnLine Course Status	.52	.48	.000	.04		
Distance Ed Status	.09	.12	.000	-.03		
InsDegAssoc	.00	.00	.000	.00		
Numeric Grade	2.92	2.99	.001	-.07		
1st Time Degree student	.35	.33	.001	.03		
White	.52	.55	.002	-.03		
Hispanic	.19	.17	.002	.02		
TotalEnrolledSemesterCredits	9.44	9.29	.003	.16		
Transfer student	.60	.62	.004	-.02		
Remedial Math Credits	.16	.14	.027	.03	These are the characteristics on which PT and FT instructors do ***NOT*** differ.	
Black	.23	.21	.100	.01		
Unknown degree status	.01	.01	.204	.00		
Otherrace	.03	.03	.231	.00		
Remedial EnglishCredits	.12	.11	.279	.01		
Non-degree student	.03	.03	.376	.00		
Remedial Student	.01	.01	.403	.00		
First Generation	.38	.38	.459	.01		
Gender	.18	.18	.564	.00		
Asian	.02	.02	.846	.00		
Age	29.62	29.64	.912	-.02		

Methodology: We used linear regression to predict final course grades, while controlling for student and instructor baseline characteristics. A treatment indicator (1,0) identifies students in the treatment (full-time) or not (part-time). Significance of the treatment variable indicates if there is a difference for part-time and full-time instructors. In determining significance levels, the *t* statistic and alpha levels of 0.05 and effect sizes (i.e., standardized mean differences) of $\geq$ 0.20 standard deviations are the criteria.

Hedges' *g* is used for effects estimates and is defined as the adjusted group mean difference divided by the unadjusted pooled within-group standard deviation (SD):

$$g = \frac{\gamma \ or \ (\overline{X}_C - \overline{X}_T)}{\sqrt{\frac{(n_C - 1)S_C^2 + (n_T - 1)S_T^2}{(n_C + n_T - 2)}}}$$

where γ is the regression coefficient for the intervention (or the mean difference) representing the group mean difference adjusted for covariates, n_C and n_T are the student sample sizes, and S_C and S_T are the final grade student-level standard deviations for the treatment and the control groups, respectively.

We specified a simple linear regression model to estimate a full-time instructor treatment effect:

$$Y_i = \gamma_0 + \gamma_1 Z_j + \sum_{h=1}^{k} \gamma_h$$

Y_i the final course grade for student *i*
γ_0 the mean covariate adjusted student final course grade
γ_1 the treatment effect of a full-time instructor on an individual's final course grade
Z_j dummy variable indicating treatment (1) with a full-time or part-time (0) instructor
$\sum_{h=1}^{k}$ the k covariates representing student and instructor characteristics
γ_h the effect of k covariates on the mean covariate adjusted student final course grade

This model includes a full-time instructor indicator and student and instructor characteristics as predictors. To determine what student and instructor variables should be included in our regression, we ran a correlation matrix with final course grade to see which variables were significantly related ($p \leq 0.05$) to final course grades (Table 4).

Table 4 *Correlations between student final course grade and student and instructor characteristics*

	Cor	***p***
TotalEarnedCredits	.19	.00
CGPA	.16	.00
White	.16	.00
AgeatCensus	.11	.00
Black	-.11	.00
transfer	.09	.00
1st time deg	-.09	.00
courselevel	.09	.00
Hispanic	-.08	.00

Pell	-.08	.00
FoundationalEnglishCredits	-.07	.00
FoundationalMathCredits	-.07	.00
OnLineCourseStatus	.07	.00
InsDegBach	.04	.00
DistanctEdStatus	.03	.00
InsDegMas	-.03	.00
InsDegUnk	-.03	.00
Instr.Status	.03	.00
Semester	.03	.00
TotalEnrolledSemesterCredits	.03	.00
FoundationalStudent	-.02	.02
Gender	-.02	.03
Otherrace	-.02	.03
IPEDTBD	-.02	.03
Asian	.01	.08
InsDegDoc	.01	.09
InsDegCert	-.01	.11
InsDegAssoc	.01	.26
IPEDNDS	-.01	.35
InstrService	.00	.89
FirstGen	.000	.962

Beginning with the variables that were significantly related to final course grades, we ran a series of regression models for all students, and for students at different course levels- freshmen, sophomores, junior, and senior. We felt the course level regressions were warranted because of the dramatic changes in instructor status and student type by course level (see table 2). Level 4 students, i.e., seniors, were not comparable to students taking level 1 (freshman) courses, nor were the nature of instructors across levels comparable either. We discarded variables from the regression if they did not have a significant coefficient or seemed redundant, and retained those that did have significant correlations with the outcome, final course grade, in the regression.

Results and Conclusions: Table 5 shows the results of the regression analysis. There is a non-significant (p = .80) full-time instructor effect of -0.01, and an effect size of -0.05. This is interpreted as a decrease of .01 on the 4.0 grade scale if a student is taught by a full time instructor, or alternatively, adjuncts give a .01 higher grade. Due to the non-significance of the instructor status effect, we conclude there is no effect for instructor status on the final course grades for these students. The R-squared (Table 6) equates to a small to moderate effect size for the model.

Table 5- *regression results- yellow equals p≤0.05*

All N=11,265			
	β	SE	*p*
(Constant)	1.05	.07	.00
TotalEarnedCredits	.00	.00	.00
GPA	.41	.01	.00
Black	-.23	.03	.00
Hispanic	-.21	.03	.00
Otherrace	-.25	.06	.00
Asian	.01	.07	.87
Age	.01	.00	.00
Pell	-.06	.02	.00
Semester	.05	.02	.01
Total Semester Credits	.03	.00	.00
Full-time instructor	-.01	.02	.80
R Square	.143		
freshman	**sophmores**	**juniors**	**seniors**
N=6,757	N=3,040	N=1,257	N=211

Using a similar approach, we created regression models for the different grade levels, and as we go up course levels (Table 6), we see that instructor status effect varies in size and direction; sometimes adjuncts give lower grades, and sometimes higher grades. There is a non-significant positive effect (adjuncts lower) at the freshmen level, a significant negative effect (adjuncts higher) at the sophomore level, and a significant positive effect (adjuncts lower) at the junior level. We did not include senior level instruction because, given Goodwin's recent transition to a four year baccalaureate institution, it was not a like-to-like comparison

Table 6 *regression results for grade levels*

freshmen	***β***	**SE**	***p***
(Constant)	2.617	.047	0.000
black	-.453	.031	.000
hispanic	-.375	.032	.000
other race	-.304	.070	.000

asian	.001	.084	.992
CGPA	.096	.008	.000
1st time deg	-.253	.025	.000
Age at Census	.013	.001	.000
Full-time instructor	.026	.026	.304
R Square	.075		
sophomores	***β***	**SE**	***p***
(Constant)	1.772	.112	.000
black	-.175	.048	.000
hispanic	-.115	.053	.031
other race	-.281	.105	.008
asian	.008	.126	.951
CGPA	.210	.017	.000
Total Enrolled Semester Credits	.045	.007	.000
Pell	-.138	.038	.000
Age	.007	.002	.001
Full-time instructor	-.074	.038	.050
R Square	.068		
juniors	***β***	**SE**	***p***
(Constant)	2.658	.117	.000
black	-.321	.062	.000
hispanic	-.401	.069	.000
other race	-.038	.152	.804
asian	-.248	.178	.164
GPA	.225	.030	.000
transfer	.207	.057	.000
Ins yrs of service	-.026	.008	.001
Full-time instructor	.142	.050	.004
R Square	.105		

Limitations: This analysis would benefit from a hierarchical level regression model, with students at level 1 and courses (*i.e.*, the instructors) at level 2, with perhaps even a third level of program or department, since the students are nested within courses within departments. This would more precisely model the effect of differing instructors on student final course grades. Course to course comparisons of part and full-time instructors would be preferable, as well, for example BIO 101 to BIO 101. Given the complexity of the educational research and the improbability of random assignment of students and instructors to control and treatment conditions, it would also be helpful to have some standardized measure of assessment that students could receive at the end of a course, perhaps making comparisons across instructors more equivalent. There is also the inherent difficulty, as seen in the preK-12 sector, of linking instructor performance with student outcomes (see Haertel, 2013). The drive for accountability in the pre-college sector has led to many attempts to assess instructor performance, and none have succeeded very well in doing that. The definition of success, the choice of the outcome measurement, and the choice of predictors can radically change how an instructor rates, providing low validity between different types of assessments of an instructor's success. It can be a fraught process.

Implications for Future Research or Current Practice: Our results may provide some guidance or insight on ways to balance the costs and productivity of full and part-time instructors to maximize student grades and satisfaction. For example, we might decide to provide full and part-time instructors with more support from our center for Teaching and Excellence, more explicitly require them to receive pedagogy training, or require full-time instructors to teach more lower level courses. Knowing how instructors perform provides useful planning information within the context of an institution's overall goals and objectives, and allows planners to rationally prioritize resource allocation to achieve institutional objectives.

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Integrative Learning: Helping Students Make the Connections

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Abstract

At the University of Michigan, research conducted with student leaders showed that even though most of these leaders reported having extraordinary learning experiences, the vast majority of them could not describe what they had learned, why or how it was valuable to them, or how they might apply their knowledge and skills. Through integrative learning, students can make meaningful connections of their experiences, synthesize their learning, and gain a greater understanding of how their skills and knowledge can help them achieve their academic, professional, and personal goals. This research explores the university’s effort to facilitate integrative learning by engaging students in a curriculum focused on guided self-reflection.

Keywords: Integrative Learning, Student Learning, Learning Outcomes, ePortfolios, Reflection

Introduction

In his attention-getting book, *Excellent Sheep*, William Deresiewicz (2014) describes students at elite institutions as “smart and talented and driven, yes, but also anxious, timid, and lost, with little intellectual curiosity and stunted sense of purpose: trapped in a bubble of privilege, heading meekly in the same direction, great at what they’re doing but with no idea why they’re doing it” (p. 3). This perspective is not unlike the results of research conducted at the University of Michigan, where interviews with student leaders that demonstrated that, while most of these students reported having “extraordinary” learning experiences at UM, they were largely unable to describe what they had learned, why or how it was valuable to them, or how they might apply their knowledge and skills they had acquired at UM once they left the university (Pathways Report, 2006). In 2006, the University of Michigan formalized an institutional effort to address these issues by establishing a model of pedagogy and technology that helps students recognize and articulate what they have learned. Known as MPortfolio, this effort utilizes ePortfolio technology and a curriculum and pedagogy focused on self-reflection to foster integrative learning, a key learning outcome focusing on students’ abilities to identify and connect their learning experiences and apply their learning to new situations.

Integrative Learning Defined

The literature on integrative learning consistently frames the discussion of the topic around the innate desire of humans to make connections and how this characteristic is central to intellectual and emotional development. Integrative learning is more than just making connections between different concepts or experiences; it also involves recognizing and evaluating the connections that we make (Huber, Hutchings, Gale, Miller, and Breen, 2007). The Association of American Colleges and Universities (AAC&U), which has been the champion of integrative learning as an important postsecondary outcome, defines integrative learning as "an understanding and a disposition that a student builds across the curriculum and co-curriculum, from making simple connections among ideas and experiences to synthesizing and transferring learning to new, complex situations within and beyond the campus" (AAC&U, 2008, p. 1). By including synthesis as a component, this definition reflects a conception of integrative learning that requires individuals to do more than tacitly transfer knowledge and skills acquired from a previous experience to a new problem. This definition also recognizes that integrative learning is not limited to students' curricular experiences. Rather, integrative learning incorporates both curricular and co-curricular experiences and the connections and synthesis of learning from these experiences can then be applied as individuals face future challenges both within and outside of postsecondary education. Mentkowski and Sharkey (2011), when describing the development of AAC&U's definition of integrative learning, underscore its complexity by describing the multiple dimensions of relationships encompassed in integrative learning: relationships among past, present, and future learning; relationships between areas of study; and relationships between prior learning and new situations where it could be used.

Integrative learning has become an intriguing, if not critical, educational outcome that colleges and universities should aim to develop in students. Given students' propensities to learn from both their curricular and co-curricular experiences, by helping students make connections between, synthesize, and evaluate the knowledge and skills they have acquired through these varied experiences, we have the potential to create a whole that is greater than the sum of its parts. In a society that is increasingly demanding of individuals in both the workplace and in civic life, it is important to educate college students so that they can adeptly face the complex challenges presented to them.

Theoretical Foundations of Integrative Learning

In order to understand integrative learning more deeply, it is helpful to review the underlying constructs that explain how individuals integrate learning. From its conception, integrative learning has been conceptualized as a multidimensional construct based on prominent theories of learning and development. Since the idea of integrative learning is still developing, there is ambiguity about the appropriate theoretical foundations. As a result, the conception of integrative learning and how to assess integrative learning are regularly up for debate.

Here, I focus on three theories that I feel best explain the processes that students go through as they demonstrate how they integrate learning. The first, transfer of learning, explains the process of connecting knowledge and skills acquired in a prior experience to new, different problems and situations. Definitions and descriptions of integrative learning frequently refer to the power of being able to make connections between different ideas and experiences. Transfer of learning is a cognitive activity based in the field of psychology that can explain how humans make connections between disparate phenomena. The study of transfer focuses on how people know and then apply their knowledge. Broadly, transfer is “the degree to which a behavior will be repeated in a new situation” (Detterman, 1993, p. 4). More specifically, when referring to transfer of learning, educational psychologists recognize it as an individual’s use of past learning when he or she learns something new and his or her application of that learning to both similar and new situations (Haskell, 2001). Individuals regularly transfer their learning from one setting to another, frequently without realizing that they are doing it. Tacit transfer may be characteristic of transfer of learning, but it is not representative of integrative learning.

According to the conception of integrative learning that I am using in the present study, the transfer of learning from prior experiences to new, different settings is an explicit cognitive process. The second theory, reflective practice (Argyris & Schön, 1974; Schön, 1983; Schön, 1987), explains this distinction. At the core of reflective practice is the idea of tacit knowledge. Tacit knowledge refers to the things that an individual knows intuitively and remain unarticulated. Attributing the concept to Polanyi (1967), Argyris and Schön (1974) describe tacit knowledge as "what we display when we recognize one face from thousands without being able to say how we do so, when we demonstrate a skill for which we cannot state an explicit program, or when we experience the intimation of a discovery we cannot put into words" (p. 10). In all of these examples, there is a sense of knowing coupled with the failure to express what it is that one knows. It is not necessarily that this knowledge is ineffable, but rather that we have internalized this knowledge to the point that it is second nature. Reflective practice assumes that an individual's tacit knowledge is frequently inconsistent with the ideas that he or she expresses externally. Reflective practice is one's effort to make tacit knowledge explicit. Engaging in the introspection associated with reflective practice forces individuals to challenge their tacit assumptions and identify discrepancies between their thoughts and behavior. This process can lead to cognitive dissonance, which leads to the third theory, self-authorship.

Where transfer can explain the breadth of individuals' application of knowledge and skills to different situations, self-authorship can explain the depth that is required of individuals as they face complex problems. When cognitive dissonance occurs, individuals who may have previously taken perspectives at face value must now reassess diverse views when it is unclear what the correct answer may be. Self-authorship is a constructive-developmental theory, focusing on how individuals grow or change in the ways they make meaning (Kegan, 1994).

Observing that existing developmental theories inappropriately compartmentalized development into discrete domains, Robert Kegan introduced self-authorship as a concept that recognizes that the development of cognitive, intrapersonal, and interpersonal domains is interconnected. The cognitive (or epistemological) dimension of self-authorship examines the basis of our beliefs and poses the question, "How do I know?" Individuals in the early stages of cognitive development assume that knowledge is certain and see the world in black and white, right and wrong. As they develop, they begin to recognize the complexity of diverse perspectives and values, first acknowledging that varying perspectives exist and eventually being able to analyze and compare conflicting opinions to understand that different viewpoints are not necessarily equally valid (Perry, 1968). The intrapersonal domain focuses on one's identity and prompts the individual to answer the question, "Who am I?" Early intrapersonal development is characterized by a lack of awareness about one's own social identity (e.g., race/ethnicity, class, sexual orientation) and a lack of understanding about other cultures. As individuals develop intraculturally, they form an internal, personal identity that is distinct from the external identity that others project upon them and begin to recognize the legitimacy of other cultures (King & Baxter Magolda, 2005). The interpersonal domain explores our relationships by asking, "How do I relate to others?" It is in this domain that individuals must confront moral and ethical ambiguity. Development in the interpersonal domain spans from judgments and values based on external societal expectations, at the lowest level of development, to defining personal values based upon principles that one has determined internally, at the highest level of development (Kohlberg, 1976). In his book *In Over Our Heads: The Mental Demands of Modern Life*, Kegan (1994) argues that the expectations of today's society, in both the workplace and life at home, are overwhelming and individuals must develop more advanced ways of knowing in order to meet these high expectations. Baxter Magolda (1998, 2001) applied this approach to human development to college students specifically. Based on multiple decades of research on the development of college students, she established a four-phase model of students' paths on the "journey toward self-authorship" (Baxter Magolda, 2001, p. 5).

Empirical Research on Integrative Learning

Peet et al. (2011) produced research that acts as a foundation for the present study. This study explores the relationship between the use of ePortfolios and the development of integrative learning at the University of Michigan. Using a pre-survey/post-survey design, the researchers had students self-report their integrative learning ability by indicating their level of agreement with 37 statements in 12 categories. Factor analysis was used to categorize these 37 items into 6 dimensions of integrative learning. On average, students demonstrated significant gains across all six factors from the pre-survey to the post-survey. These gains were consistent across all groups of students as there were no significant differences based on class year, gender, race/ethnicity, and survey year. Where there was a difference that was both statistically and practically significant was that gains were pronounced among students who participated in more than one MPortfolio course or program. Additionally, there were differences based on academic field. Students in the natural sciences experienced the greatest gains in demonstrating knowledge gained within and across specific contexts, recognizing and adapting to differences, understanding and directing oneself as a learner, and identifying and discerning their own and others' ethics and perspectives. Humanities students, on the other hand, gained the most in becoming reflexive, accountable, and relational learners. The consistent and broad gains provide compelling evidence that ePortfolios contribute to the development of integrative learning. The authors recognized that the study was merely "the first step within a much larger research effort that is focused on developing theory, identifying best practices, and creating effective assessment instruments for fostering integrative knowledge and lifelong learning across a wide range schools, disciplines and institutions" (p. 21).

Integrative learning has become a part of multiple large-scale studies. Notably, the National Survey of Student Engagement (NSSE) includes a set of questions related to integrative learning in its DEEP Learning section (Documenting Effective Educational Practice). In this section, students are asked how often they engaged in a variety of activities during the most recent academic year. The section includes questions related to the application of knowledge and skills from different contexts to new situations (e.g., working on a paper or project that required integrating ideas or information from various sources, putting together ideas or concepts from different courses when completing assignments or during class discussions). Consistent with AAC&U's statement on integrative learning, one item addresses whether students utilize diverse and contradictory points of view: including diverse perspectives (different races, religions, genders, political beliefs, etc.) in class discussions or writing assignments. Finally, two questions focus on whether students extend their curricular learning beyond the traditional confines of the classroom (i.e., discussing ideas from readings or classes with faculty outside of class; discussing ideas from readings or classes with others outside of class). The survey prompts students to indicate the frequency of these activities on a four-point scale, ranging from "very little" to "very much." These questions have also been utilized in the Wabash National Study of Liberal Arts Education. These are both large, multi-institutional studies and each has presented conclusions about integrative learning in peer-reviewed journals and for the improvement of academic programs at the institution level.

Multiple studies utilizing NSSE data include integrative learning as an outcome. The first of these studies sheds light on how integrative learning is associated with other collegiate outcomes and whether these relationships vary based on academic discipline (Nelson Laird, Shoup, Kuh, and Schwarz, 2008). Using data from both NSSE and the Faculty Survey of Student Engagement (FSSE), the authors found a positive relationship between engagement in integrative learning activities and personal and intellectual development, student satisfaction, and grades. Regarding differences by discipline, both seniors and faculty reported that there was significantly less engagement in integrative learning activities in hard fields (e.g., biology, mathematics, medicine) compared to soft fields (e.g., psychology, history, economics). Exploring differences based on discipline in the relationship between engagement in integrative learning activities and other outcomes, differences in personal and intellectual development tended to be minimal; the one significant difference was that the positive relationship between integrative learning and personal and intellectual development was significantly greater for students in hard applied life fields compared to those in the hard pure non-life fields. Differences based on discipline were more pronounced for the other outcomes, satisfaction and grades. The relationship between engagement in integrative learning activities and student satisfaction was strongest for students in the hard applied non-life fields. For grades, the relationship was strongest for students in the soft pure life and soft pure non-life fields. Nelson Laird and Garver (2010) built upon the previous study by introducing an additional dimension, whether there is variation between general education courses and non-general education courses. Holding all else constant, faculty teaching general education courses emphasized integrative learning, on average, significantly more than faculty teaching non-general education courses and that there were significant differences based on discipline, particularly for hard applied life fields. The authors recommend that faculty and administrators take into account disciplinary contexts when engaging in curriculum reform, particularly as they consider general education courses. In another study resulting from the NSSE survey, Zhao and Kuh (2004) found that, for both first-year students and seniors, there was a significant positive relationship between experience in a learning community and academic integration.

Based on data collected through the Wabash National Study of Liberal Arts Education, which uses the same scale as NSSE, Mayhew, Seifert, Pascarella, Nelson Laird, and Blaich (2011) explored the relationship between deep learning approaches and students' moral reasoning at the end of the first year. Controlling for student background, pre-college factors, and first-year coursework there was a significant positive relationship between engagement in integrative learning activities and moral reasoning. For the other deep approaches, higher-order learning and reflective learning, the relationships with moral reasoning were not statistically significant. Aside from this study, the relationship between integrative learning and moral reasoning is one that is largely unexplored. However, the results support one finding about interpersonal development that was previously generated through research at Alverno College. Mentkowski and Associates (2000) found, through student interviews, that students at Alverno developed an appreciation of differing values because they were consistently asked to examine and discuss them across multiple contexts. While this study provides evidence that a relationship between integrative learning and moral reasoning exists, even after controlling for other deep approaches, the authors provide little insight into the mechanisms that theoretically explain this relationship other than that a relationship should plausibly exist.

Barber (2012) used longitudinal qualitative data gathered in the Wabash National Study of Liberal Arts Education to investigate integration of learning. He analyzed interviews with 97 students at liberal arts colleges with the goal of understanding how college students connect knowledge and experiences and so that educators can more intentionally promote the integration of learning. Through this analysis, he found that there were three distinct types of integration. The first, establishing a connection, is characterized by the discovery of similarities between ideas though the ideas remain distinct. In this category, students compare and contrast, use analogies and similes, and make connections between concepts. The second type, application across contexts, is characterized by the use of knowledge from one context in a different context. This type of integration often appeared when students described how they used skills or knowledge that they acquired in high school in collegiate settings. The third type, synthesis of a new whole, is characterized by the creation of new knowledge by combining insights. Students who exhibited this type of integration used language such as "incorporate," "adapt," "collaborate," and "interpret." The students in the study most frequently fell into the second category, application across contexts, and Barber also found that students were more likely to demonstrate synthesis in the second year of the study compared to the first.

In another paper based on the data collected through the Wabash Study, Barnhardt, Lindsay, and King (2006) used a mixed-methods approach to improve our understanding of how college students integrate learning. For the quantitative analysis, the researchers constructed a seven-item scale to serve as a measure of integration of learning. This scale was comprised of items similar to those in the five-item NSSE integrative learning scale and there are two items that appear on both scales. The scales differ in that the NSSE scale has a stronger emphasis on discussions, with the assumption that discussing ideas inside and outside of the classroom is an indicator of integration of learning. The scale utilized in this study does not emphasize discussions but rather includes items that directly address the connections students make from different experiences. It also includes one item goes beyond the behaviors of students and the connections that they make and addresses the highest order of integrative learning (according to the AAC&U VALUE rubric): synthesizing and organizing ideas, information, or experiences into new, more complex interpretations and relationships. The results of the analysis revealed that interventions such as experience in a learning community, diverse interactions, and integrative assignments were significantly and positively associated with integration of learning. Additionally, sociocultural values and intercultural values and attitudes were also significant, positive predictors of integration. A student's class year was also a strong predictor of his or her level of integration. The qualitative results of the study generally supported the quantitative findings. In particular, the interview data brought to life the considerable differences based on class year, with seniors demonstrating the most evidence of integration.

A recurring theme in the empirical literature on integrative learning is that educators can create settings and interventions that may effectively facilitate integrative learning. Melendez, Bowman, Erickson, and Swim (2009) explored the impact of one intervention, a short-term multidisciplinary problem-solving experience at the United States Military Academy, on students' capacity to integrate learning. This experience was seven days long, incorporated multidisciplinary activities, and explicitly focused on the connections between mathematics and biology. The goal of this effort was "to create an integrative learning experience (ILE) that better prepared our students to respond effectively to the uncertainties of a changing technological, social, political and economic world" (p. 132). The authors noted that students generally had a positive experience, though there was no evidence of whether the intervention resulted in the enhancement of students' integrative learning or any other educational outcomes. Faculty indicated that the experience was initially unsettling, as they were forced to approach their teaching in a new way. However, they quickly adapted and, in the end, reported that the experience was positive. While this article did not provide quantitative evidence supporting the experience, it is a good example of the types of interventions that colleges and universities can pilot as they try to facilitate integrative learning.

ePortfolios in Action on the University of Michigan Campus

In 2006, the University of Michigan formalized its institutional effort around ePortfolios with the MPortfolio project. A joint effort of the Division of Student Affairs and the Office of the Provost, MPortfolio was established with the aim of fostering integrative learning in order to help students recognize and articulate what they have learned during their time at the University of Michigan. Portfolio work has long existed at the University of Michigan within a diverse set of academic units, each with its own unique set of learning outcomes. Some units use portfolios as tools for assessing hard skills, while others employ portfolios that are professionally focused. For example, the Sweetland Writing Center requires students in the Writing 220 course to complete ePortfolios that encourage students to reflect on their work so that they improve their writing skills. Professional portfolios, such as the ones that the School of Education uses for its aspiring teachers, act as a showcase of student work that they can use to demonstrate their skills, abilities, and experiences to potential employers. A third type of ePortfolio, the integrative learning portfolio, compels students to reflect on their disparate experiences (e.g., coursework, co-curricular activities, key personal events) so that they gain a greater understanding of their skills, knowledge and values and can articulate a personal philosophy statement. Some academic units incorporate a hybrid model in their portfolio work. For example, the School of Information utilizes an integrative learning portfolio as part of its professionally-oriented Practical Engagement Program (PEP), which enrolls master's students participating in credit-based internships, and students in the School of Dentistry must create an ePortfolio that requires students to reflect and draw connections between their coursework and real world experiences as well as monitor the competencies that they are expected to develop through the programs. The common thread that runs throughout each of these types of portfolio work is that it encourages students to grow through self-reflection.

The Division of Student Affairs (DSA) at the University of Michigan has embraced integrative learning as a desired outcome of undergraduate students at the institution. By developing integrative learning in students, DSA expects that students will be able to make meaningful connections of their experiences, synthesize their learning, and gain a greater understanding of how their skills and knowledge can help them achieve their academic, professional, and personal goals. As a champion of integrative learning on campus, DSA has been instrumental in promoting integrative learning as “a process for synthesizing learning across multiple experiences, coalescing meaning, and also creating new learning and meaning” (Taylor, 2011).

Empirical Research on ePortfolios

In addition to the aforementioned study by Peet et al. (2011), several other studies have explored the impacts of the use of ePortfolios on student outcomes in postsecondary education, though these studies have been especially lacking in academic rigor. Desmet, Church Miller, Griffin, Balthazor, and Cummings (2008) conducted the most rigorous of these studies and found that, when used to support writing instruction, the use of ePortfolios was correlated with an overall mean increase in the quality of essays, though about a quarter of the students saw declines in quality of their essays. In a similar study focused on secondary students transitioning into higher education, Acker and Halasek (2008) found that student writing improved between the initial draft and the final essay, but they attributed student gains to the quantity and quality of feedback rather than the ePortfolio technology itself. They proposed that it was a useful tool for structuring the learning environment and facilitating the feedback and rewriting processes. Neither of these studies used a control group. There were two other studies that tied student achievement to the use of ePortfolios, but these studies were more descriptive in nature. Crawford (2003) reported that, based on early anecdotal results of ePortfolio implementation at Hocking College in Ohio, the use of portfolios is positively associated with gains in communication skills. Cambridge (2008), in a descriptive article on the use of ePortfolios at George Mason University, indicated that portfolio assessment has been useful in helping students achieve the nine core competencies expected of students in the institution's New Century College, though the article did not report to what extent and in what ways portfolios influenced student achievement.

Research Questions

The overarching question addressed by this research is: *To what extent do ePortfolios facilitate the development of integrative learning?* Accordingly, all of the research conducted in this study is designed to answer this central research question. Using a pre-/post-survey design, I investigate whether students' integrative learning ability changes between the start and the end of the process of developing a reflective ePortfolio. In addition to aiding the program evaluation efforts of MPortfolio, I expect that answering this research question will result in contributions to both the body of literature exploring the influence of assessment on student achievement and also the emerging body of literature on integrative learning.

In order to organize the research in a manageable way and to develop a more fully formed understanding about specific aspects of MPortfolio, a series of sub-questions will guide the inquiry proposed in the overarching research question. The goal of the first sub-question (*"What is the causal impact of ePortfolio use on students' integrative learning?"*) is to determine whether the relationship between engagement in a reflective ePortfolio process and integrative learning is causal. In other words, can one plausibly attribute the development of integrative learning to this particular experience rather than all of the other curricular, co-curricular, social, and personal things happening in the lives of college students? Previous research at the University of Michigan has demonstrated that students experience positive changes in integrative learning over the course of the MPortfolio experience (Peet et al., 2011). However, without a control group, this research does not demonstrate whether the gains associated with MPortfolio are any different from the changes that the students may have experienced without engaging in the MPortfolio process.

Finally, the purpose of the second sub-question (*"Does the development that students experience persist beyond their initial experiences using ePortfolios?"*) is to determine whether the learning that students experience through the MPortfolio process stays with them years after the initial experience or whether it fades away over time. The research design employed in this study is a pre-/post-survey design, with surveys administered at the start of the process and again at the end. With this design, it provides evidence about how students change over the course of the experience but does not demonstrate whether students retain what they learn beyond this experience. The present study also includes a follow-up survey two years after the completion of the experience to determine whether the changes persist. This has the potential to be a compelling contribution to the research since implicit in the integrative learning outcome of this study are habits of mind that students should carry with them through their lives.

Conceptual Framework

Though Banta (2002) found that assessment practitioners frequently approach their work without utilizing a theoretical framework, there is a vast collection of theories that can guide assessment efforts. I review two theories that I believe are especially applicable for understanding how ePortfolios, and the MPortfolio process specifically, can contribute to integrative learning. First, I describe and critique Astin's (1970a, 1970b, 1976, 1993) input-environment-output (I-E-O) model, which is frequently used in higher education research to understand how institutional environments influence the outcomes of students. Second, I describe how Kolb's (1984) Experiential Learning Theory explains how the reflective processes of MPortfolio can contribute to student learning.

Banta (2002) conducted an informal poll of colleagues and found that, although most campuses did not employ a conceptual framework to guide their assessment efforts, those who did were likely to have implemented Astin's Input-Environment-Outcome (I-E-O) model. Based on organizational input-process-output (I-P-O) models, the I-E-O model is a traditional systems model that identifies the system's inputs and outputs and the processes that the inputs go through in order to be transformed into the outputs. In the case of Astin's model, the inputs refer to student demographic characteristics, family background, and pre-college academic and social experiences. The environment includes the various programs, policies, cultures, faculty, peers, and experiences that students encounter while they are in college. Outcomes, as described in the introduction, encompass students' knowledge, skills, attitudes, values, and behaviors at the completion of their studies and beyond. According to the model (illustrated in Figure 1), inputs both shape outcomes directly and influence outcomes indirectly through the ways in which students engage with the campus environment. Astin's model takes a value-added approach, defining a student's change or growth during college as a comparison of his or her outcome characteristics with his or her input characteristics. Astin (1993) explains that "the basic purpose of the model is to assess the impact of various environmental experiences by determining whether students grow or change differently under varying environmental conditions" (p. 7). Studying the impact of a college education with the I-E-O model can help faculty, administrators, and policy makers identify the programs and policies that best serve students in their achievement of educational outcomes.

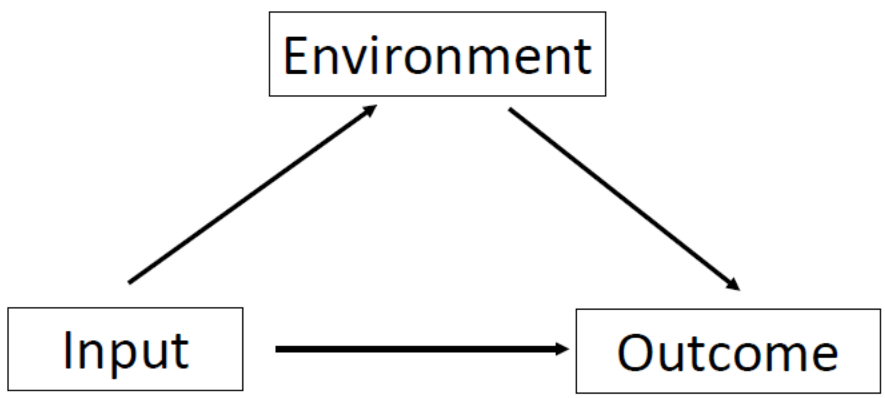

Figure 1: Input-Environment-Outcome (I-E-O) Model (Astin, 1970a, 1970b, 1977, 1993)

Astin's I-E-O model explains how an institutional environment, broadly, can influence student outcomes. Assessment is a feature of the institutional environment, though it is merely one of many aspects of the environment that students experience during their time at the college. The second theory that I present as a way to explain how assessment can influence student achievement is more directly focused on how ePortfolio assessment, and the MPortfolio process in particular, can contribute to integrative learning. To put it succinctly, MPortfolio is a process that encourages students to reflect upon their experiences so that they have a greater understanding of themselves. While the ePortfolio tool is integral to MPortfolio, the process relies at least as much on the curriculum and pedagogy that guide it. At the heart of all three of these components – pedagogy, curriculum, and the ePortfolio tool – is reflection. The curriculum consists of a series of exercises aimed at having students reflect upon their experiences so that they are able to identify their knowledge, skills, and values, understand how the experiences that have developed their knowledge, skills, and values are connected, and be able to apply what they have learned to new settings. The pedagogy, facilitated by faculty, staff, or peers, provides scaffolding and guides the reflective process. Recognized as a reflective tool, the ePortfolio technology allows students to organize and reflect upon their experiences and then highlight what they have learned through the process.

Nearly a century ago, John Dewey (1916) established a link between reflection and learning, positing that reflection is a critical part of the learning process. To paraphrase Dewey, we do not learn from experience; it is by reflecting on our experiences that we learn. Dewey (1933) defines reflective thought as "active, persistent, and careful consideration of any belief or supposed form of knowledge in the light of the grounds that support it, and the further conclusions to which it tends" (p. 6). Rogers (2001), reviewing and synthesizing prominent conceptualizations of reflection, proposes that reflection is:

> a cognitive or affective process or activity that (1) requires active engagement on the part of the individual; (2) is triggered by an unusual or perplexing situation or experience; (3) involves examining one's responses, beliefs, and premises in light of the situation at hand; and (4) results in integration of the new understanding into one's experience. (p. 41)

Further, Rogers posits that the ultimate intent of reflection is to integrate the understanding one has gained from his or her experiences so that he or she can make better choices or actions and enhance his or her overall effectiveness. Kolb's (1984) Experiential Learning Theory is a useful way to conceptualize how the reflective activities of the MPortfolio process could facilitate student learning. Building off the work of Dewey, Kurt Lewin, and Jean Piaget, Kolb developed a cyclical four-component model that aims to explain how individuals learn from their experiences. According to Experiential Learning Theory, learning is defined as "the process whereby knowledge is created through the transformation of experience" (p. 38). Accordingly, while Kolb's model can begin at any one of its four points, it is helpful to conceptualize its start with the concrete experiences that individuals have at the start of the learning process. During the second step of the model (reflective observation), individuals make observations about and reflect upon these concrete experiences. In the third step (abstract conceptualization), individuals learn from the experience by forming abstract concepts and generalizations. It is during this step that individuals make connections, conscious or subconscious, between actions and the effects of these actions. In the fourth step (active experimentation), individuals apply what they have learned by testing the implications of these concepts in new situations. The cycle returns to the first stage as individuals have new experiences in which they have applied what they have learned through the process. Figure 2 illustrates this cycle.

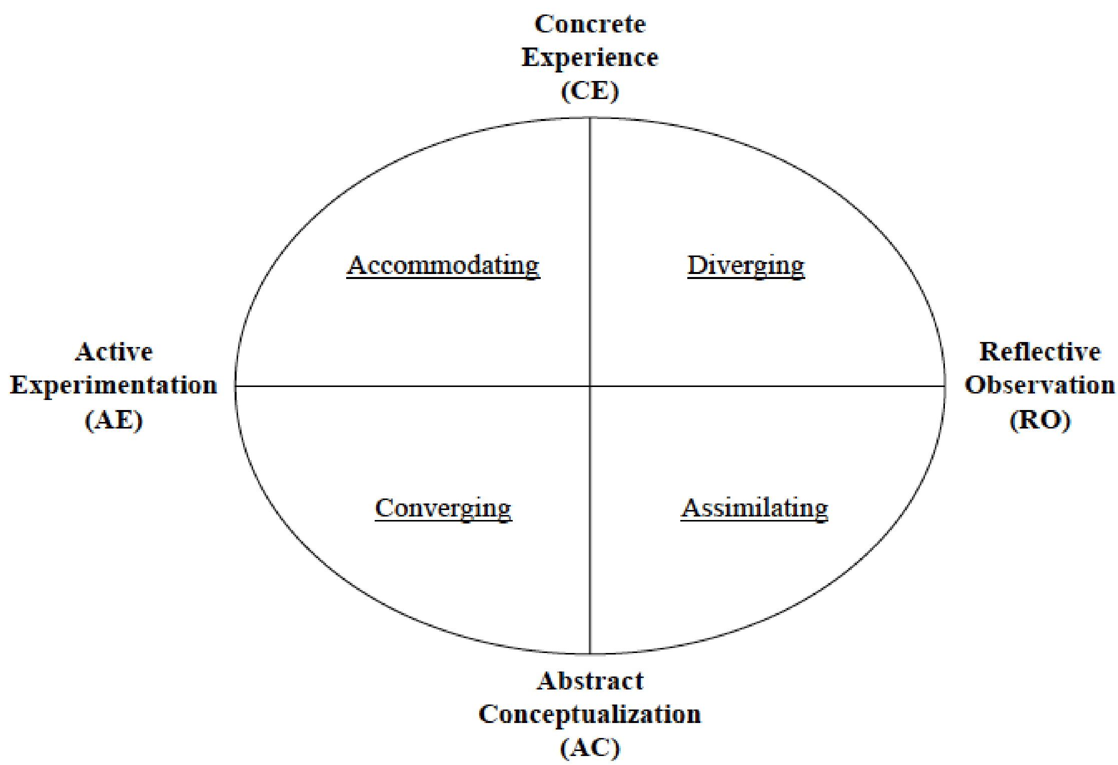

Figure 2: The Experiential Learning Cycle and Basic Learning Styles (Kolb, 1984)

This theory is particularly helpful in understanding how students who go through reflective ePortfolio processes can transform the experiences they have at the beginning of the experience to a deeper understanding of themselves at the end. Through the process at the University of Michigan, students are typically asked to identify experiences that are important to them and then reflect on these experiences to develop new knowledge by recognizing what is meaningful about these experiences. For example, when developing a personal Philosophy Statement, students are asked to describe experiences during which they felt "deeply engaged or purposeful." Reflecting on their observations about these important experiences, they are then asked to identify themes so they can identify the meaningful aspects of these experiences. An anecdote that has been compelling to practitioners engaged in this work on the University of Michigan campus is that feedback from employers to Career Services has indicated that students would receive an A-plus on their resumes but are failing their interviews. On their resumes, they have accumulated a strong collection of concrete experiences; however, they have difficulty articulating what is meaningful about these experiences when they meet with employers. The process of developing an ePortfolio helps students go from being able only to cite these concrete experiences to being able to describe the skills and knowledge they have developed through their experiences, how these experiences relate to each other, and how they can apply what they have learned to new settings. Additionally, by teaching students how to reflect and encouraging them to continue to use their ePortfolios as a tool for reflection, students learn to take their newly developed knowledge and begin the cycle again.

Data & Methods

Since 2009, research on integrative learning at the University of Michigan has employed a longitudinal survey design to determine how students' abilities to integrate their learning change. Over this period, 1,600 students completed a baseline pre-survey at the start of the MPortfolio process and a post-survey at the end. The main instrument used in this study is the Integrative Learning Self-Assessment. This survey instrument is based upon the AAC&U integrative learning VALUE rubric and has been utilized in MPortfolio research efforts since 2009. A team of researchers at the University of Michigan, comprised of Simone Himbeault Taylor, Malinda Matney, Patricia Gurin, Melissa Peet, Steve Lonn, and Tiffany Marra, designed the Integrative Learning Self-Assessment to measure the conceptual dimensions of integrative learning. When administered at different points in time, this self-assessment allows researchers to measure the changes that students experience in multiple dimensions of integrative learning over the course of a learning experience. The core of the survey is composed of 37 statements in 12 categories with which students are asked to indicate their level of agreement on a five-point

Likert scale (from “strongly disagree” to “strongly agree”). Two years later, a group of students responds to a follow-up survey to determine whether changes persist beyond the initial experience. The research also includes a delayed-treatment, control group design that can determine whether there is a causal relationship between engagement in the process and integrative learning. The pre-survey response rate has been 85% and the post-survey response rate has been 80%. Matching the pre-survey responses to the post-survey responses, the overall matched response rate is 71%. The response rate for the follow-up survey was 30%, considerably lower though reasonable given that the students’ distance from the initial MPortfolio experience and that quite a few students had already graduated and were no longer on campus.

The pre-/post-survey design of the study aims to measure how students change over the course of the MPortfolio process. Students commence the process with a set of background characteristics and experiences. Since the MPortfolio is an inductive learning process that focuses on students’ reflections on their identity and experiences, it is assumed that the background characteristics and experiences they bring to the process are elements that are critical to integrative learning through MPortfolio. The pre-survey, administered when students begin the process, serves a baseline measure of integrative learning. After engaging in the MPortfolio process, students complete the post-survey, which is the source of the dimensions of integrative

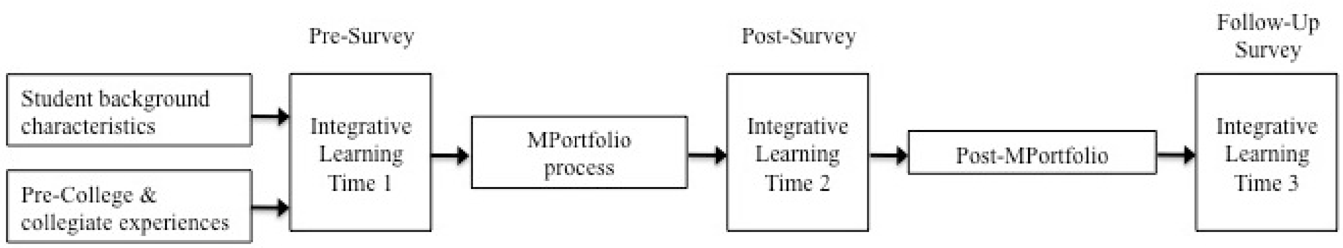

Figure 3: Conceptual Model of Correlational Research Design

learning that serve as the intended outcomes of the process. Beginning during the 2012-13 academic year, students who engaged in MPortfolio through the Division of Student Affairs two years prior completed a follow-up survey to determine how students' integrative learning ability changes beyond the immediate MPortfolio experience and whether they continue to engage in the reflective activities they learned through the process and if they continue to update and utilize their ePortfolios. Data from these three surveys comprise the data set for the current study. Figure 3 is a model of the research design that provides a visualization of the timing and elements of the study.

The goal of this design is to demonstrate how students change throughout this process. However, without a control group of students who have not engaged in MPortfolio, it is impossible to determine whether the changes that students potentially experience are different from the development that college students might otherwise experience without going through this process. In order to determine whether integrative learning can be attributed to the MPortfolio process, it is necessary to determine how students who engage in the process develop differently from equivalent students who do not

In order to determine the causal impact of MPortfolio on integrative learning, it is necessary to compare students who engage in the process (the treatment group) to a group of students that is essentially the same but do not engage in the MPortfolio experience (the control group). It is not enough to compare these groups on observable characteristics such as gender, race, major, or grade point average. Such a design can suffer from omitted variable bias. For example, the fact that students elect to participate in MPortfolio may be indicative of a greater level of motivation compared to students who do not participate. Thus, it is possible that this difference in motivation could explain any observed differences in integrative learning. To make a compelling causal claim, it is important to eliminate such threats to validity by minimizing the differences between the treatment and control groups for both observable and unobservable characteristics.

The gold standard for causal research is a randomized controlled trial (RCT), an experimental design in which a group of subjects is randomly divided into a treatment group and a control group. These two groups are the same with the one exception that the treatment group receives the treatment (in this case, engagement in MPortfolio) and the control group does not. It has not been possible to arrange for an RCT to determine the effect of MPortfolio, since the institutional leaders who are responsible for it do not want to exclude interested students from the process. In the absence of an RCT, I employ a design that assigns students to treatment and control groups, minimizes omitted variable bias, and allows all students who are interested in MPortfolio to engage in the process.

The causal component of this research includes only the students who engage in MPortfolio through the Psych 322: First-Year Experience course. Offered in both the Fall term and the Winter term, first-year students engage in this 1- or 2-credit course in a residence hall-based, peer-facilitated experience over 6 weeks. The fact that this course is offered both in the Fall and the Winter allows for the possibility to utilize a delayed treatment, control group research design. Figure 4 provides a visualization of this research design. In this design, the students who participated in the course during the Fall term serve as the treatment group, while those who participated during the Winter term serve as the control group during the Fall term (prior to their own participation). Students in the Fall course completed the pre-survey and the post-survey according to the standard Fall survey administration schedule (at the start of the experience in October and again at the end in December). Students in the Winter course cohort completed a pre-survey when the Fall course began and, when they enrolled in the course during the Winter term, they completed the pre-survey again at the start of the experience in January and the post-survey at the end of the experience in March. This design allows me to compare a group of students who have selected into the MPortfolio process and engage during the Fall term to a group of students who also select into MPortfolio but do not participate in the Fall. Using two groups who select into the process minimizes the omitted variable bias associated with selection differences. One could argue that the two groups are inherently different because one group has chosen to participate in the Fall and, for some unknown reason, the other group has decided to put off its engagement until the Winter. However, the main reason why one group

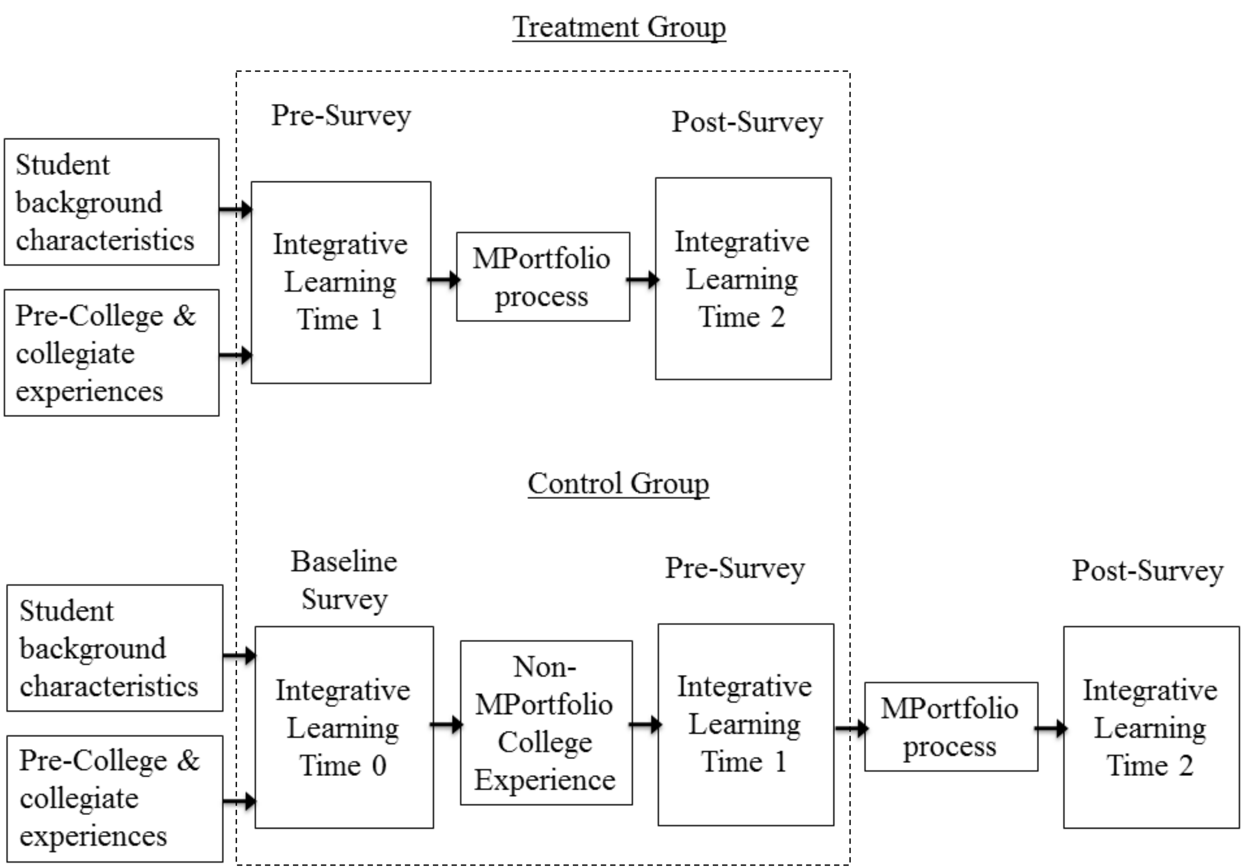

Figure 4: Conceptual Model of Causal Research Design

participates in the Fall and the other participates in the Winter is based on the Resident Advisor who leads the process. Some of the Resident Advisors choose to lead the process in the Fall, while others choose to do so in the Winter. Since the students are randomly assigned to both their residence halls and their Resident Advisors, whether they participate during the Fall or the Winter appears to be unrelated to the integrative learning outcome.

To reduce the 37 survey items into a smaller set of dimensions of integrative learning, I conducted exploratory factor analysis using principal component analysis and varimax rotation with Kaiser normalization. Based on evaluation of Eigenvalues (greater than 1) and visualization of the scree plot, I identified five factors that explain 60% of the variance. After exploring how each factor and the items that loaded highly on each factor aligned with the theoretical constructs of integrative learning, I named each factor: 1) Identify knowledge, skills, and values, 2) Provide evidence of knowledge, skills, and values to others, 3) Recognize and adapt to differences in order to create solutions, 4) Work with others to identify and address complex problems, and 5) Develop a professional digital identity. I then computed composite scores, or scales, based on the mean of the items that had their primary loadings on each factor. These scales, which I refer to as dimensions of integrative learning, include all 37 survey items and each item is unique to a particular dimension of integrative learning. Dimensions include items with factor loadings of at least .42. Each dimension of integrative learning had a high level of reliability, as evidenced by Cronbach's alpha values exceeding .80.

The first dimension of integrative learning is *Identify knowledge, skills, and values*. The common theme that appeared in this dimension's items is students' abilities to identify what they have learned—knowledge, skills, values, passions, interests, strengths, etc. This ability to identify what one has learned is a product of the reflective process that transforms tacit knowledge to explicit knowledge. Through this greater understanding of oneself, a student can recognize how his or her beliefs and values inform his or her life, recognize the strengths and weaknesses he or she brings to learning and work situations, and explore the ways in which he or she can enhance these strengths or address these weaknesses. Recalling the AAC&U VALUE Rubric for integrative learning, identification is a benchmark level of performance (the lowest level out of four ordered categories of performance): "Identifies connections between life experiences and those academic texts and ideas perceived as similar and related to own interests" (AAC&U, 2009, p. 2).

The second dimension builds upon identifying knowledge, skills, and values to being able to *provide evidence of knowledge, skills, and values to others*. This dimension consists of 12 items, so it encompasses a broad range of student abilities. While the items in this dimension feature a variety of student outcomes and activities (e.g., personal values and beliefs, knowledge and skills, learning from and working with others) within and across specific contexts, the common thread across the items is the student's ability to demonstrate what he or she has learned. Eleven of the dimension's 12 items include either "provide evidence" or "demonstrate" in the item's language. The AAC&U Integrative Learning VALUE Rubric explicitly addresses the ability to demonstrate integration in a criterion called "Integrated Communication." At the most basic level, students should have the capacity to complete the assignment in "an appropriate form." However, for students to exhibit higher levels of performance, their demonstration of integration should explicitly connect content and form and purposefully enhance meaning for the audience.

The third dimension, *Recognize and adapt to differences in order to create solutions*, emphasizes students' understanding about how identity shapes their worldview and the opportunities and challenges associated with working with people different from oneself. This dimension of integrative learning demonstrates the relational emphasis of the Integrative Learning Self-Assessment. The dimension represents the interpersonal and intrapersonal domains of self-authorship and recognizes that integration is not merely the connection of ideas and experiences; accounting for context and understanding how one's learning connects to their own perspectives and the perspectives of others are qualities that are critical for addressing complex problems in the 21st century.

The fourth dimension, *Work with others to identify and address complex problems*, builds upon the previous dimension. Once a student recognizes the importance of understanding context and how individuals' perspectives are informed by their backgrounds and experiences, can he or she then work with others to identify and address complex problems? This dimension includes a variety of activities related to working with others to solve problems: collaboratively identifying problems and developing plans and taking action to address the problems, taking into account the needs and perspectives of all group members, being mindful of the ways in which other group members are engaging, and seeking feedback from others.

The fifth dimension, *Develop a professional digital identity*, is similar to the second dimension (*Provide evidence of knowledge, skills, and values to others*) in that it highlights the importance of being able to provide evidence of integration in a coherent and meaningful way. Consisting of only 3 items, this dimension includes developing and continually updating a professional identity online (i.e., through an ePortfolio or personal website) that demonstrates one's knowledge, skills, and values. Additionally, one item in this dimension specifies that this online professional identity should be different from one's personal Facebook account.

To analyze the data, I employ two main analytic approaches. First, I use paired-samples t-tests to explore change from the pre-survey to the post-survey. Second, I use repeated measures ANOVAs to determine the treatment effect and long-term impact.

Results

First, I address the overarching research question of the study, *to what extent do ePortfolios facilitate the development of integrative learning?* In order to understand whether engagement in the MPortfolio process is associated with integrative learning, I have performed a series of paired samples t-tests on the overall sample of students who engaged in MPortfolio and completed both the pre-survey and the post-survey. This procedure demonstrates whether the mean post-survey dimensions of integrative learning are significantly different from the equivalent means from the pre-survey. In other words, on average, do students experience significant changes in the dimensions of integrative learning from the start of the MPortfolio process to the end?

Table 1 presents the mean values for each dimension of integrative learning from both the pre-survey and the post-survey, as well as the difference between these two values. Additionally, the table indicates whether these mean differences are statistically significant and the effect sizes of the changes. The results of the paired samples t-test suggest that, on average, students who engage in MPortfolio experience significant positive changes across all five dimensions of integrative learning. Based on the effect size values, gains ranged from fairly small to moderate. Students most improved their ability to provide evidence of knowledge, skills, and values to others (Cohen's $d = .539$), while the smallest gains were related to students' ability to recognize and adapt to differences in order to create solutions (Cohen's $d = .244$).

Table 1: Paired Samples T-Tests of Pre- and Post-Survey Dimensions of Integrative Learning				
Dimension of Integrative Learning	Pre-Survey Mean (Standard Deviation)	Post-Survey Mean (Standard Deviation)	Mean Difference	Effect size (Cohen's d)
Dimension 1: Identify knowledge, skills, and values	4.257 (0.472)	4.436 (0.459)	0.179***	0.375
Dimension 2: Provide evidence of knowledge, skills, and values to others	3.911 (0.655)	4.261 (0.572)	0.349***	0.539
Dimension 3: Recognize and adapt to differences in order to create solutions	4.427 (0.431)	4.536 (0.444)	0.109***	0.244
Dimension 4: Work with others to identify and address complex problems	4.243 (0.482)	4.401 (0.476)	0.158***	0.309
Dimension 5: Develop a professional digital identity	3.563 (0.916)	4.029 (0.845)	0.466***	0.468

***p< 001

Focusing on the pre-survey mean values, it is striking how high the pre-survey means are; the scale for each dimension spans from 1 to 5 and three of the five dimensions have pre-survey means greater than 4. With pre-survey means greater than 4 and the highest scale value capped at 5, there is not much room to increase. Despite this potential limitation, there were significant positive changes for all five dimensions of integrative learning. At the same time, while a potential ceiling effect did not contribute to a lack of statistical significance, it may have tempered the effect sizes of the dimensions that had high mean pre-survey values.

Next, I present the results of the causal research design. While previously the results demonstrated that students experience significant positive changes in all five dimensions of integrative learning, it is impossible to determine from those results that the change can be attributed to the MPortfolio process or that the change is a result of a variety of other factors in students' lives. The delayed treatment control group design eliminates selection bias by comparing a treatment group of students who experience the MPortfolio process to a control group of students who have not yet participated in the process.

Comparing the two groups on observable characteristics, they appear to be the same. Regarding academic ability, the mean composite ACT scores for the treatment (M = 29.5) and control (M=29.4) groups were not significantly different (p=.902). Since this comparison was made during the first semester of the first year, it is not possible to make comparisons based on grade point average. Regarding demographics, the groups were similarly composed, which chi-square tests revealing no significant differences by sex or race. Females comprised 72.9% of the treatment group and 63.6% of the control group (p=.540). Due to the small size of the control group, I aggregated students of color into a single group, which comprised 26.7% of the treatment group and 18.2% of the control group (p=.560). There were no international students in the control group and international students accounted for only 4.3% of the treatment group.

The next comparison of the treatment and control groups is concerning the dimensions of integrative learning at the time of the pre-survey for the treatment group and the baseline survey, prior to enrolling in the course, for the control group. Table 2 presents the means for each dimension for the treatment and control groups and the difference between the group means. For four of the five dimensions of integrative learning, there were no significant differences between the treatment and control groups at Time 1 of the causal design. The one exception was Dimension 1: Identify knowledge, skills, and values. For this dimension, students in the control group had a significantly higher baseline mean than the treatment group.

Table 2: Dimensions of Integrative Learning at Baseline, Treatment and Control Groups			
Dimension of Integrative Learning	Treatment Mean (Standard Deviation)	Control Mean (Standard Deviation)	Mean Difference
Dimension 1: Identify knowledge, skills, and values	3.961 (0.516)	4.377 (0.340)	-0.415*
Dimension 2: Provide evidence of knowledge, skills, and values to others	3.681 (0.611)	3.835 (0.400)	-0.154
Dimension 3: Recognize and adapt to differences in order to create solutions	4.266 (0.490)	4.352 (0.487)	-0.087
Dimension 4: Work with others to identify and address complex problems	4.098 (0.467)	4.104 (0.561)	-0.006
Dimension 5: Develop a professional digital identity	3.438 (0.884)	3.455 (0.910)	-0.017

* Significant at .05 level

Table 3 shows that, for Dimension 1: Identify knowledge, skills, and values, there was a significant main effect for the change from Time 1 to Time 2, $F(1, 57) = 5.268$, $p<.05$, $\eta2=.085$. This result demonstrates that the total sample of both the treatment group and the control group experienced a significant positive change. The within-subjects interaction of time and treatment is the key component of the analysis, as it determines whether the treatment and control groups experience significantly different changes from Time 1 to Time 2. In other words, based on this

Table 3: Repeated Measures ANOVA to Demonstate the Effect of MPortfolio on Integrative Learning, Dimension 1: Identify knowledge, skills, and values

	df	MS	F	p		η^2
Within-Subjects						
Time	1	0.629	5.268	0.025	*	0.085
Time*Treatment	1	4.008	33.554	<0.001	***	0.371
Error (MPortfolio)	57	0.119				
Between-Subjects						
Treatment	1	0.060	0.194	0.662		0.003
Error	57	0.310				

* Significant at .05 level
*** Significant at .001 level

research design, this interaction reveals whether there is a causal relationship between engagement in the MPortfolio process and integrative learning. The significance of the interaction, $F(1, 57) = 33.554$, $p<.001$, $\eta2=.371$, provides evidence that MPortfolio effects students' abilities to identify their knowledge, skills, and values.

Figure 5 illustrates how the treatment group and the control group change from Time 1 to Time 2. As noted above, compared to the treatment group, the control group had a significantly higher mean value for this dimension at Time 1. A paired-samples t-test of the treatment group revealed a significant positive change from the pre-survey to the post-survey ($p<.001$). At the

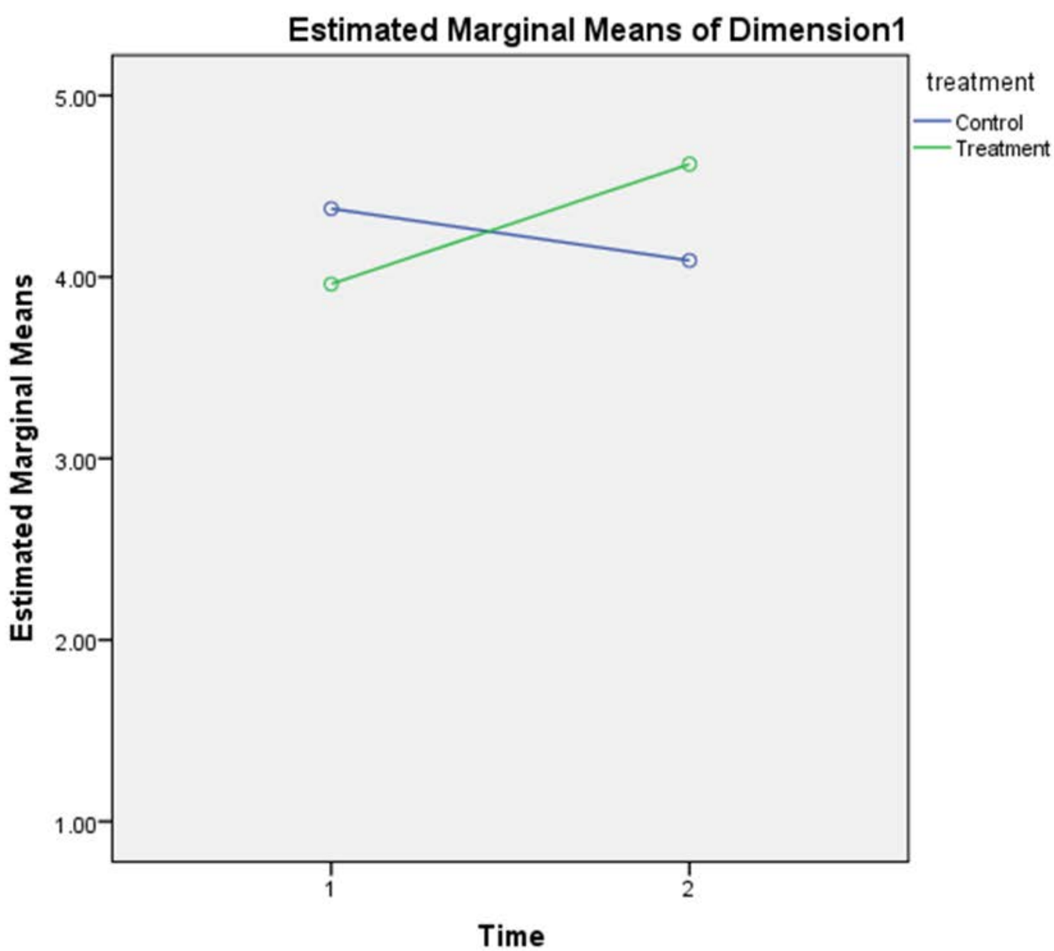

Figure 5: Effect of MPortfolio on Dimension 1: Identify knowledge, skills, and values

same time, students in the control group demonstrated a significant decline ($p<.05$) from Time 1, when they took the baseline survey prior to their enrollment in the course, and Time 2, when they took the pre-survey.

The results of the causal model for Dimension 2: Provide evidence of knowledge, skills, and values to others are featured in Table 4. Again, there is a significant main effect that demonstrates that the total sample of both treatment and control groups experienced a significant positive change from Time 1 to Time 2, $F(1, 57) = 13.876$, $p<.001$, $\eta2=.196$. Most importantly, the interaction between time and treatment provides evidence that there is a causal relationship between engagement in MPortfolio and the development of students' abilities to provide evidence of their knowledge, skills, and values to others, $F(1, 57) = 21.375$, $p<.001$, $\eta2=.273$. There was also a significant between-subjects difference, according to the model. This between-subjects test tells us that the treatment and control groups have significantly different mean values for Dimension 2, when averaged across both time points. The between-subjects differences revealed in this and the other repeated measures ANOVA models are not useful for answering this study's research questions since the research questions are concerned with change from Time 1 to Time 2 rather than average differences over time.

Table 4: Repeated Measures ANOVA to Demonstrate the Effect of MPortfolio on Integrative Learning, Dimension 2: Provide evidence of knowledge, skills, and values to others

	df	MS	F	p		η^2
Within-Subjects						
Time	1	2.621	13.876	<0.001	***	0.196
Time*Treatment	1	4.038	21.375	<0.001	***	0.273
Error (MPortfolio)	57	0.189				
Between-Subjects						
Treatment	1	1.842	4.948	0.03	*	0.08
Error	57	0.372				

* Significant at .05 level
*** Significant at .001 level

Figure 6 visualizes the effect of MPortfolio on students' abilities to provide evidence of their knowledge, skills, and values to others. At Time 1, there was no significant difference between the treatment and control groups ($Mean_{treatment}$=3.68, $Mean_{control}$=3.83, p=.429). Using a paired-samples t-test to compare the means of Time 1 and Time 2, there was no significant difference for the control group (p=.364). For the treatment group, there was a significant positive change from Time 1 to Time 2 (p<.001).

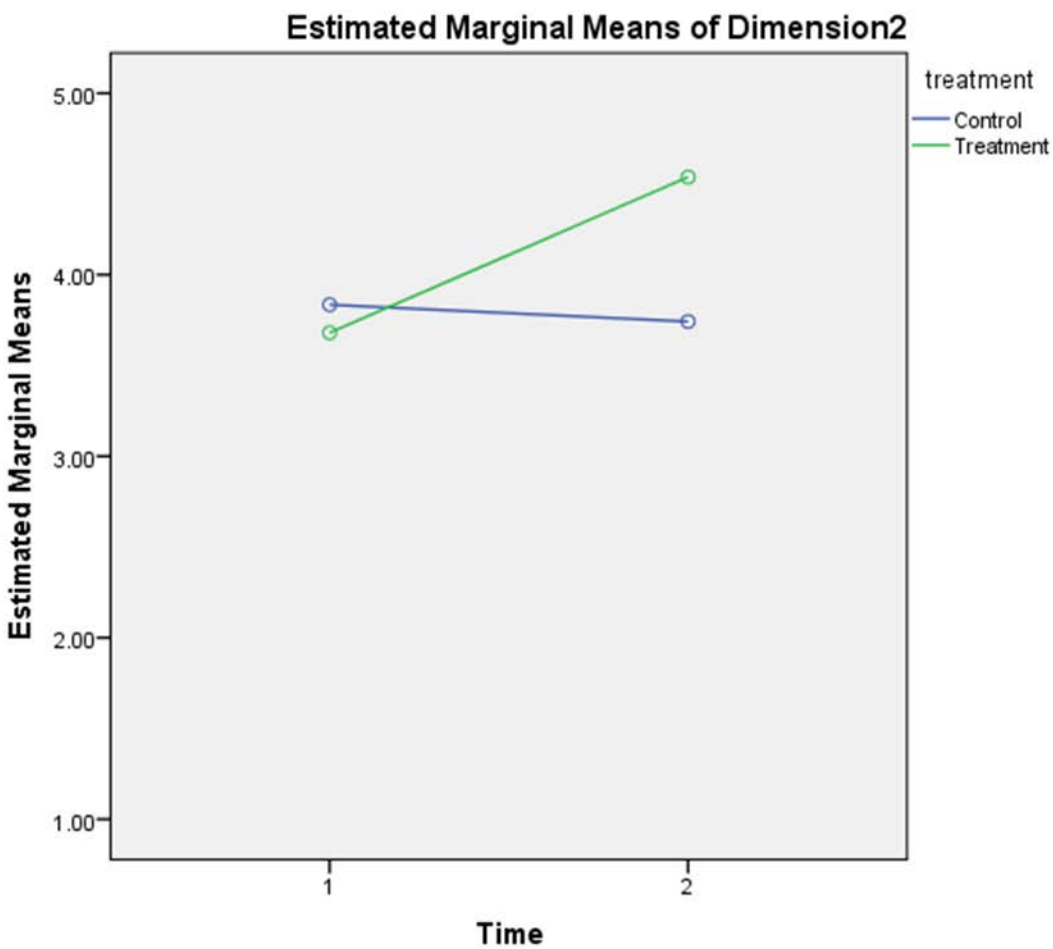

Figure 6: Effect of MPortfolio on Dimension 2: Provide evidence of knowledge, skills, and values to others

For Dimension 3: Recognize and adapt to differences in order to create solutions, there was also a significant positive effect associated with engagement in the MPortfolio process, F (1, 57) = 12.63, p<.001, $\eta 2$=.181. See Table 5 for the complete model results. Figure 7 provides a visual of the changes that the treatment and control groups for Dimension 3. On average, this is the dimension in which students reported having the strongest ability at Time 1. Comparing the two groups, there was no significant difference at Time 1 between the treatment and control groups ($Mean_{t1}$=4.27, $Mean_{c1}$=4.35, p=.598). The treatment group experienced a significant positive change from Time 1 to Time 2 ($Mean_{t1}$=4.27, $Mean_{t2}$=4.62, p<.001), while there was slight, non-significant decline between Time 1 and Time 2 for the control group ($Mean_{t1}$=4.35, $Mean_{t2}$=4.18, p=.192).

Table 5: Repeated Measures ANOVA to Demonstrate the Effect of MPortfolio on Integrative Learning, Dimension 3: Recognize and adapt to differences in order to create solutions

	df	MS	F	p		η^2
Within-Subjects						
Time	1	0.155	1.577	0.214		0.027
Time*Treatment	1	1.244	12.63	0.001	**	0.181
Error (MPortfolio)	57	0.098				
Between-Subjects						
Treatment	1	0.561	1.952	0.168		0.033
Error	57	0.287				

** Significant at .01 level

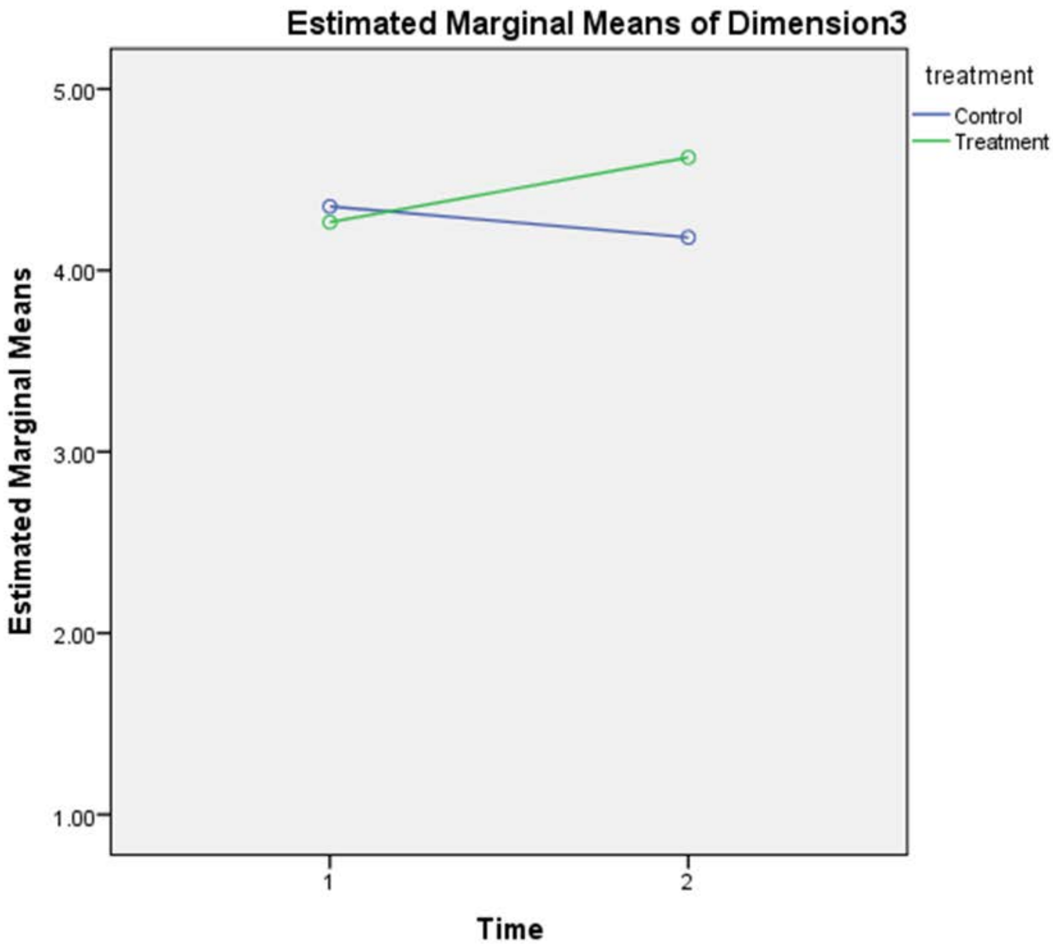

Figure 7: Effect of MPortfolio on Dimension 3: Recognize and adapt to differences in order to create solutions

There was also a significant positive effect for the fourth dimension of integrative learning, work with others to identify and address complex problems. Reported in detail in Table 6, in addition to there being a significant positive main effect for time, $F (1, 57) = 4.946$, $p<.05$, $\eta2=.080$, the interaction between time and the treatment reveals that there is a causal relationship between engagement in MPortfolio and students' abilities to work with others to identify and address complex problems, $F (1, 57) = 9.382$, $p<.01$, $\eta2=.141$. At Time 1, the mean Dimension 4 value was 4.10 for both the treatment group and the control group ($p=.972$). From

Time 1 to Time 2, the mean for the control group declined slightly and non-significantly to 4.026 (p=.671), while the mean for the treatment group increased significantly to 4.589 (p<.001).

Table 6: Repeated Measures ANOVA to Demonstrate the Effect of MPortfolio on Integrative Learning, Dimension 4: Work with others to identify and address complex problems

	df	MS	F	p		η^2
Within-Subjects						
Time	1	0.764	4.946	0.030	*	0.080
Time*Treatment	1	1.449	9.382	0.003	**	0.141
Error (MPortfolio)	57	0.154				
Between-Subjects						
Treatment	1	1.391	4.659	0.035	*	0.076
Error	57	0.299				

* Significant at .05 level
** Significant at .01 level

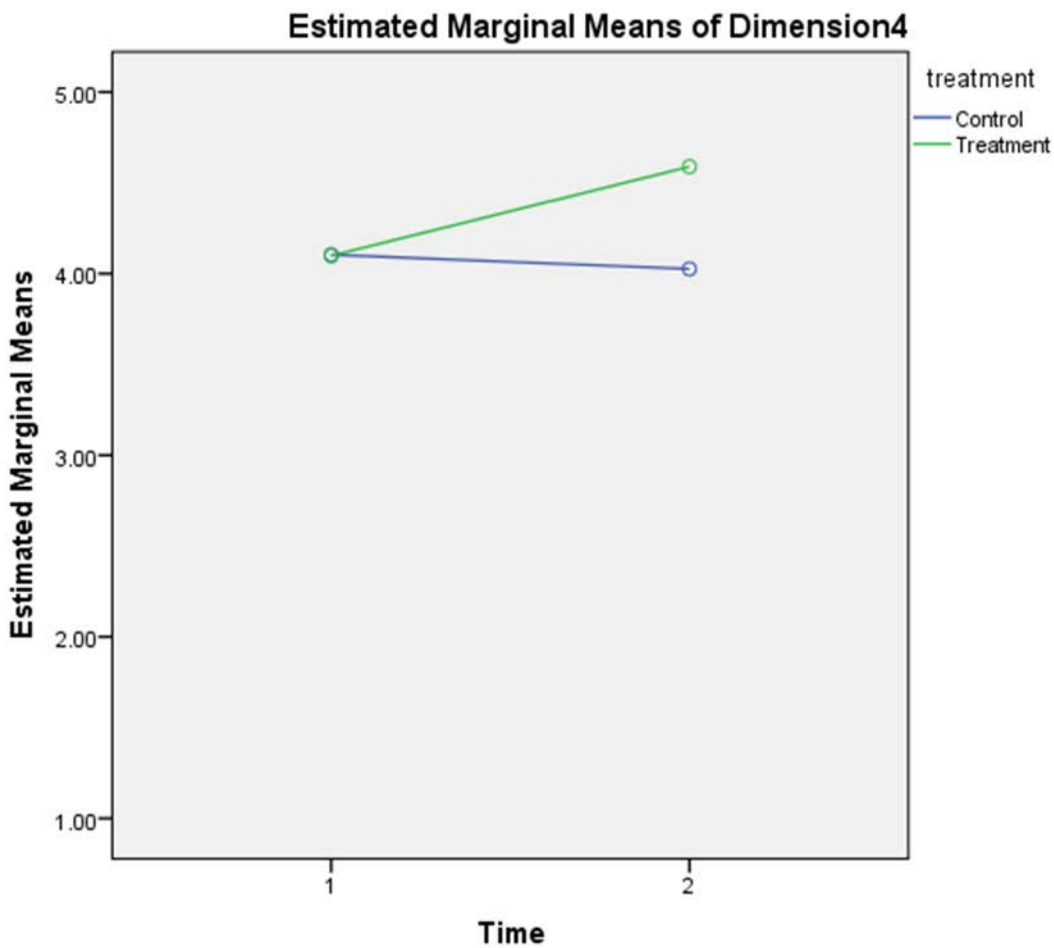

Figure 8: Effect of MPortfolio on Dimension 4: Work with others to identify and address complex problems

The results for Dimension 5: Develop a professional digital identity were a bit different from the results for the other four dimensions. Table 7 shows that there was a significant main effect for time, $F(1, 57) = 11.55$, $p<.01$, $\eta 2=.168$, meaning that the combined treatment and control groups experienced a significant positive change from Time 1 to Time 2. The interaction between time and treatment, indicating whether there is a causal relationship, was only marginally significant, $F(1, 57) = 3.594$, $p<.10$, $\eta 2=.059$. At Time 1, the mean Dimension 5 values for the treatment and control groups were not only not significantly difficult but they were also nearly identical ($Mean_{t1}=3.438$, $Mean_{c1}=3.456$, $p=.954$). From Time 1 to Time 2, each group saw a positive change, as depicted in Figure 9. The change for the treatment group was significant ($Mean_{t1}=3.438$, $Mean_{t2}=4.292$, $p<.001$), while the increase for the control group was not significant ($Mean_{c1}=3.455$, $Mean_{c2}=3.697$, $p<.233$).

Table 7: Repeated Measures ANOVA to Demonstrate the Effect of MPortfolio on Integrative Learning, Dimension 5: Develop a professional digital identity

	df	MS	F	p		η^2
Within-Subjects						
Time	1	5.381	11.55	0.001	**	0.168
Time*Treatment	1	1.675	3.594	0.063	~	0.059
Error (MPortfolio)	57	0.466				
Between-Subjects						
Treatment	1	1.493	1.995	0.163		0.034
Error	57	0.749				

~ Significant at .10 level
* Significant at .05 level
** Significant at .01 level
*** Significant at .001 level

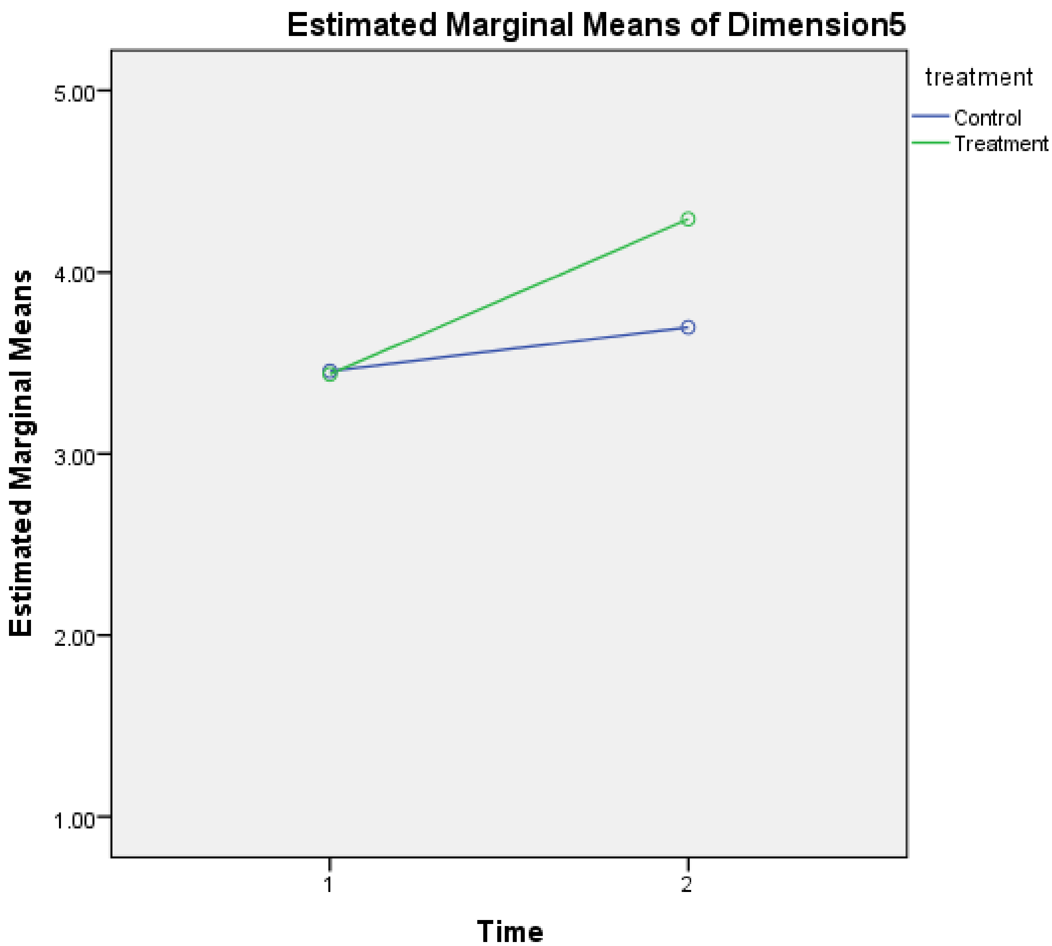

Figure 9: Effect of MPortfolio on Dimension 5: Develop a professional digital identity

Finally, I answer the research sub-question, "Does the development that students experience persist beyond their initial experiences using ePortfolios?" Having established that students experience significant positive changes across all five dimensions of integrative learning, this question aims to determine whether students' learning gains are lasting. These results are based on the responses of students who responded to the pre-survey, the post-survey, and a follow-up survey two years after their MPortfolio experience. Unlike previous results, the time effect explored in this design is a three-level effect (i.e., pre-survey, post-survey, follow-up survey) demonstrating how integrative learning changes over two time periods. The first time period occurred during the MPortfolio process and the second occurred from the time the MPortfolio process ends to approximately two years later at the time of the follow-up survey.

Table 8 presents the mean values for each dimension of integrative learning at the pre-survey, post-survey, and follow-up survey for the analytic sample used to answer this research sub-question. Again, the main statistical approach is a repeated-measures ANOVA. For a three-level design, a significant main effect indicates only that a significant different exists from one level to another, but the procedure does not reveal whether the difference is between $time_1$ and $time_2$ or between $time_2$ and $time_3$. After establishing whether the main effect is significant, I then use paired-samples t-tests to identify the differences. Another difference related to a three-level repeated-measures ANOVA is that the assumption of sphericity applies, since there are now multiple combinations of levels and the variances of these differences must be roughly equal. Unless indicated otherwise, the statistical models do not violate the assumption of sphericity.

Table 8: Mean Dimensions of Integrative Learning, Pre-Survey to Post-Survey to Follow-Up Survey			
	Pre-Survey Mean (Std Dev)	Post-Survey Mean (Std Dev)	Follow-Up Survey Mean (Std Dev)
Dimension 1: Identify knowledge, skills, and values	4.194 (0.456)	4.429 (0.411)	4.421 (0.405)
Dimension 2: Provide evidence of knowledge, skills, and values to others	3.796 (0.762)	4.308 (0.519)	4.110 (0.592)
Dimension 3: Recognize and adapt to differences in order to create solutions	4.368 (0.426)	4.544 (0.456)	4.528 (0.424)
Dimension 4: Work with others to identify and address complex problems	4.201 (0.471)	4.419 (0.440)	4.368 (0.469)
Dimension 5: Develop a professional digital identity	3.350 (0.940)	3.960 (0.856)	3.209 (1.171)

For Dimension 1: Identify knowledge, skills, and values, there was a significant main effect for time, $F(2, 116)=12.219$, $p<.001$, $\eta2=.174$. Reviewing the plot that illustrates the changes in value from pre-survey to post-survey to follow-up survey (Figure 10), it appears that students markedly increased their mean values for Dimension 1 from the pre-survey to the post-survey and the change from the post-survey to the follow-up survey two years later was minimal. The paired-samples t-test confirms this. There was a significant positive increase in the mean value over the course of the MPortfolio process ($Mean_{t1}=4.194$, $Mean_{t2}=4.429$, $p<.001$). While there was a very slight decline from the post-survey to the follow-up survey, these means were not significantly different ($Mean_{t2}=4.429$, $Mean_{t3}=4.421$, $p=.890$). Further, students' self-reported ability to identify their knowledge, skills, and values was significantly higher at the time of the follow-up survey compared to the start of the MPortfolio process ($Mean_{t1}=4.194$, $Mean_{t3}=4.421$, $p<.001$).

Table 9: Three-Level Repeated Measures ANOVA for Integrative Learning, Dimension 1: Identify knowledge, skills, and values

	df	MS	F	p		η^2
Within-Subjects						
Time	2	1.052	12.219	<.001	***	0.174
Error(Time)	116	0.860				

*** Significant at .001 level

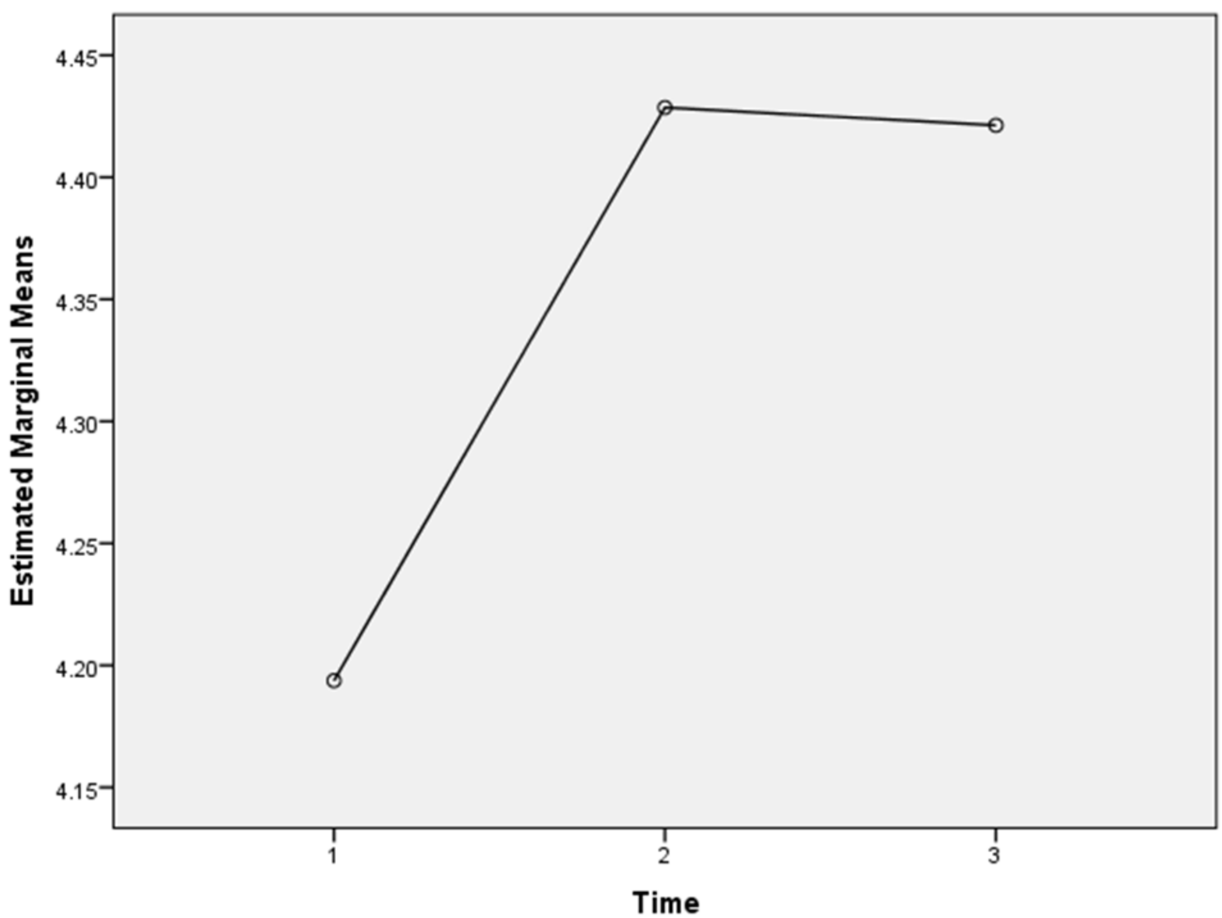

Figure 10: Change of Integrative Learning Dimension 1: Identify knowledge, skills, and values, from Pre-Survey to Post-Survey to Follow-Up Survey

There was a different pattern exhibited for Dimension 2: Provide evidence of knowledge, skills, and values to others. For the repeated measures ANOVA, Mauchly's Test of Sphericity was significant (W=.884, χ^2=7.035, p=.030) indicated the sphericity assumption was violated, so the Greenhouse-Geisser estimates were interpreted to correct for this violation. The model indicated that there was a significant time effect, F (1.792, 116) =16.492, p<.001, η2=.221, and the plot in Figure 11 demonstrates an increase in the mean Dimension 2 value from the pre-survey to the post-survey and a decrease from the post-survey to the follow-up survey. The paired samples t-tests show that students' reported a significantly stronger ability to provide evidence of knowledge, skills, and values at the end of the MPortfolio process compared to the start ($Mean_{t1}$=3.796, $Mean_{t2}$=4.308, p<.001). The decrease in the mean value from the post-survey to the follow-up survey was also significant ($Mean_{t2}$=4.308, $Mean_{t3}$=4.110, p=.011). Although this was a significant decline, the mean on the follow-up survey was still significantly higher than the pre-survey mean value ($Mean_{t1}$=3.796, $Mean_{t3}$=4.110, p=.001). These results indicate that the learning gains related to the ability to provide evidence of knowledge, skills, and values begin to fade in the two years after the MPortfolio experience; however, two years later this ability is still significantly stronger than it was at the start of the process.

Table 10: Three-Level Repeated Measures ANOVA for Integrative Learning, Dimension 2: Provide evidence of knowledge, skills, and values to others

	df	MS	F	p		η^2
Within-Subjects						
Time	1.792	4.391	16.492	<.001	***	0.221
Error(Time)	116	0.239				

*** Significant at .001 level

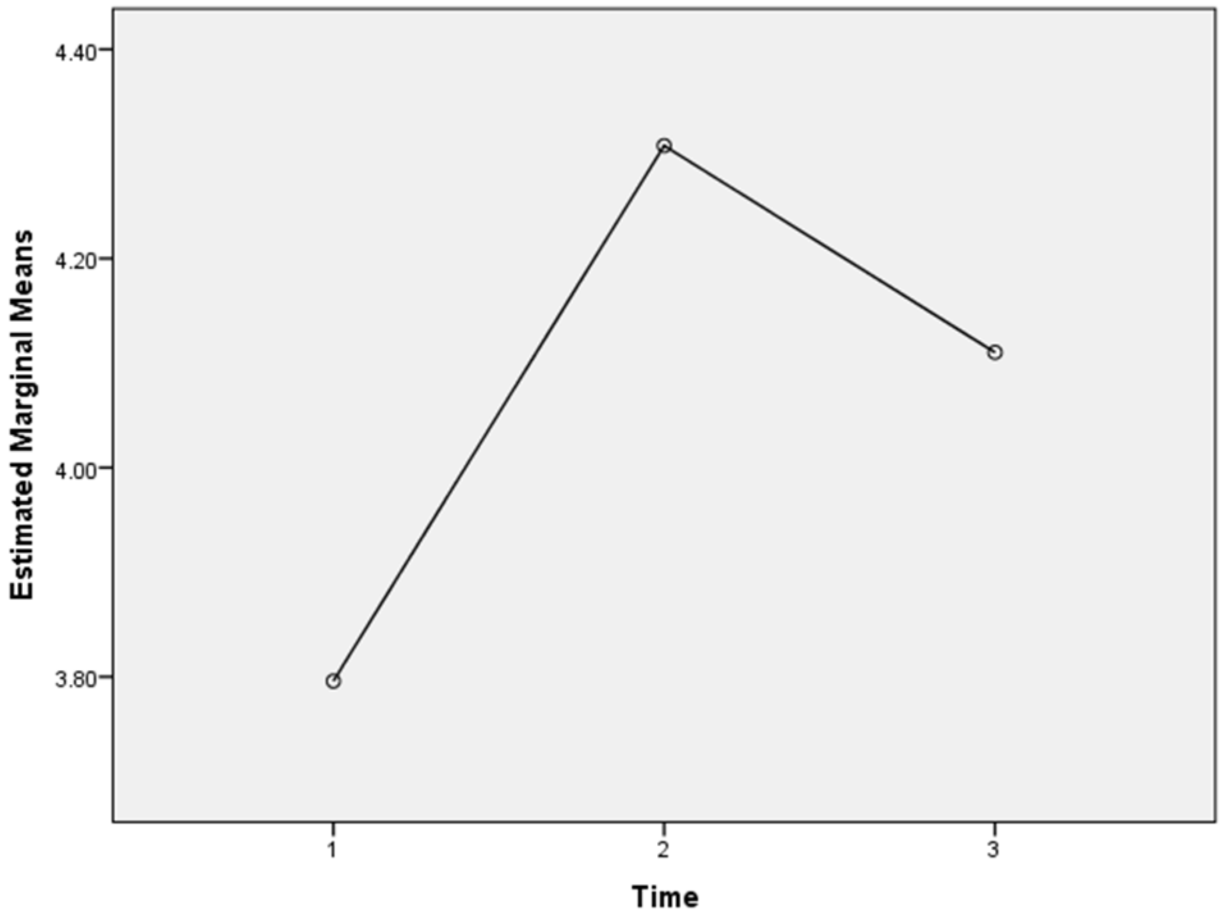

Figure 11: Change of Integrative Learning Dimension 2: Provide evidence of knowledge, skills, and values to others, from Pre-Survey to Post-Survey to Follow-Up Survey

The pattern for Dimension 3: Recognize and adapt to differences in order to create solutions resembled that of Dimension 1; there was a notable increase from the pre-survey mean to the post-survey mean and there was a slight decrease from the post-survey to the follow-up survey (see Figure 12). The model described in Table 11 indicates that there is a main time effect, $F\ (2, 116) = 6.718$, $p=.002$, $\eta 2=.104$, meaning that students' self-reported abilities to recognize and adapt to differences in order to create solutions change over time. The paired samples t-tests reveal that the mean value from the post-survey is significantly higher than the mean value on the pre-survey ($Mean_{t1}=4.368$, $Mean_{t2}=4.544$, $p=.002$) and there was no significant difference between the post-survey and the follow-up survey values ($Mean_{t2}$=4.544, $Mean_{t3}$=4.528, p=.742). Comparing the pre-survey to the follow-up survey, students' self-reported abilities to recognize and adapt to differences were significantly stronger, on average, on the latter survey ($Mean_{t1}$=4.368, $Mean_{t3}$=4.528, p=.004).

Table 11: Three-Level Repeated Measures ANOVA for Integrative Learning, Dimension 3: Recognize and adapt to differences in order to create solutions

	df	MS	F	p		η^2
Within-Subjects						
Time	2	0.560	6.718	0.002	**	0.104
Error(Time)	116	0.083				

** Significant at .01 level

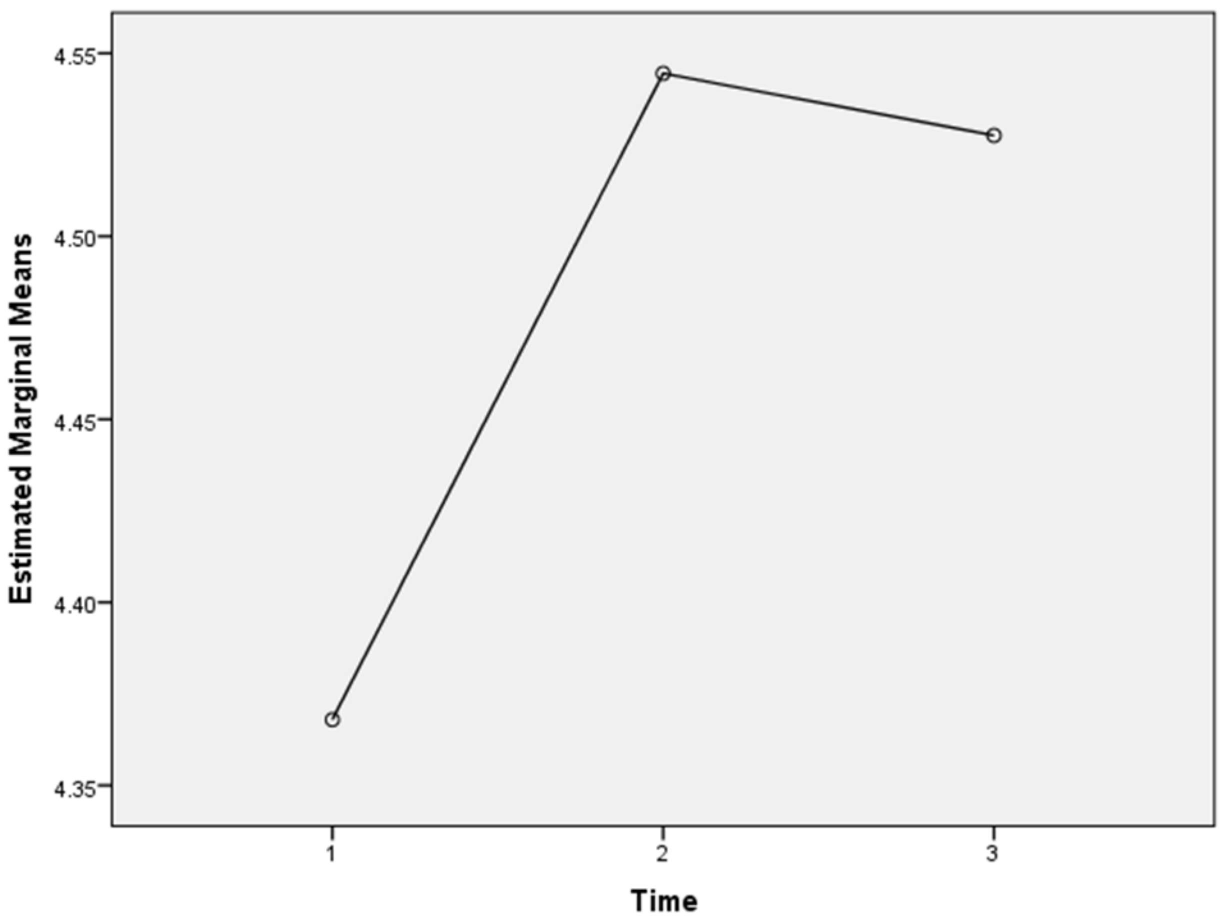

Figure 12: Change of Integrative Learning Dimension 3: Recognize and adapt to differences in order to create solutions, from Pre-Survey to Post-Survey to Follow-Up Survey

Reported in Table 12, there was also a significant main effect for Dimension 4: Work with others to identify and address complex problems, $F(2, 112) = 6.718$, $p=.001$, $\eta2=.115$. For this dimension, there was a significant increase from the pre-survey mean value to the post-survey ($Mean_{t1}=4.201$, $Mean_{t2}=4.419$, $p=.001$). Again, while there was a slight decrease from the post-survey to the follow-up survey, these means were not significantly different ($Mean_{t2}=4.419$, $Mean_{t3}=4.368$, $p=.367$). Finally, comparing the pre-survey and follow-up survey results, students reported significantly stronger abilities to work with others to identify and address complex problems two years after going through the MPortfolio process ($Mean_{t1}=4.201$, $Mean_{t3}=4.368$, $p=.014$). Figure 13 represents the change that students experience for Dimension 4: Work with others to identify and address complex problems.

Table 12: Three-Level Repeated Measures ANOVA for Integrative Learning, Dimension 4: Work with others to identify and address complex problems

	df	MS	F	p		η^2
Within-Subjects						
Time	2	0.560	6.718	0.001	**	0.115
Error(Time)	112	0.114				

** Significant at .01 level

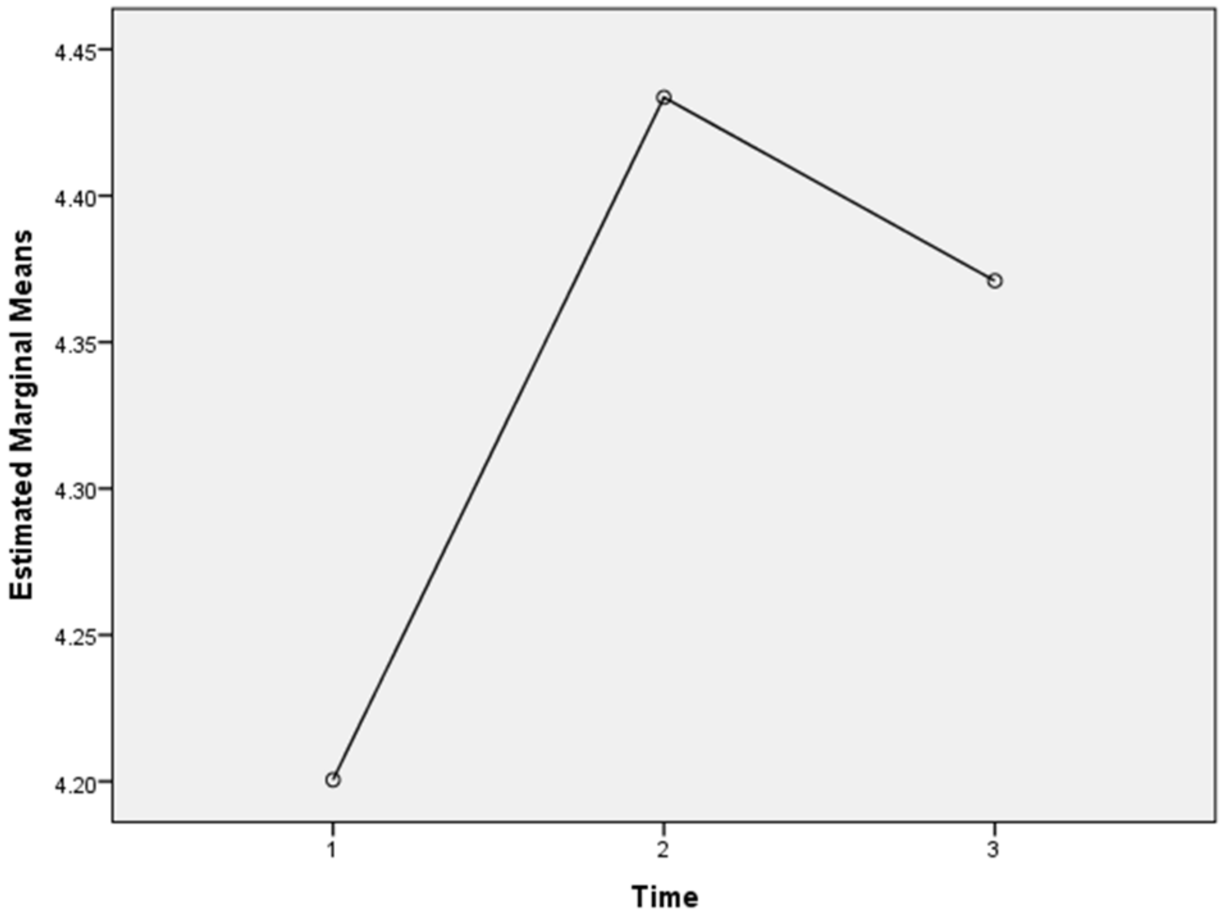

Figure 13: Change of Integrative Learning Dimension 4: Work with others to identify and address complex problems

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Table 13 shows that, for Dimension 5: Develop a professional digital identity, there was a significant main effect, $F(2, 116) = 13.396$, $p<.001$, $\eta2=.118$. However, Figure 14 demonstrates that the change that students experience is different from what they undergo with other dimensions of integrative learning. Like the other dimensions, the post-survey mean was significantly higher than the pre-survey mean ($Mean_{t1}=3.350$, $Mean_{t2}=3.960$, $p<.001$). From the post-survey to the follow-up survey, there was a significant decrease ($Mean_{t2}=3.960$, $Mean_{t3}=3.209$, $p<.001$) in the mean for develop a professional digital identity. Two years after the MPortfolio process, students reported that, on average, their ability to develop a professional digital identity was no different from when they started MPortfolio ($Mean_{t1}$=3.350, $Mean_{t3}$=3.209, p=.389). This means that students' learning gains related to developing a professional digital identity evaporated within two years.

Table 13: Three-Level Repeated Measures ANOVA for Integrative Learning, Dimension 5: Develop a professional digital identity

	df	MS	F	p		η^2
Within-Subjects						
Time	2	9.409	13.396	<.001	***	0.118
Error(Time)	116	0.702				

*** Significant at .001 level

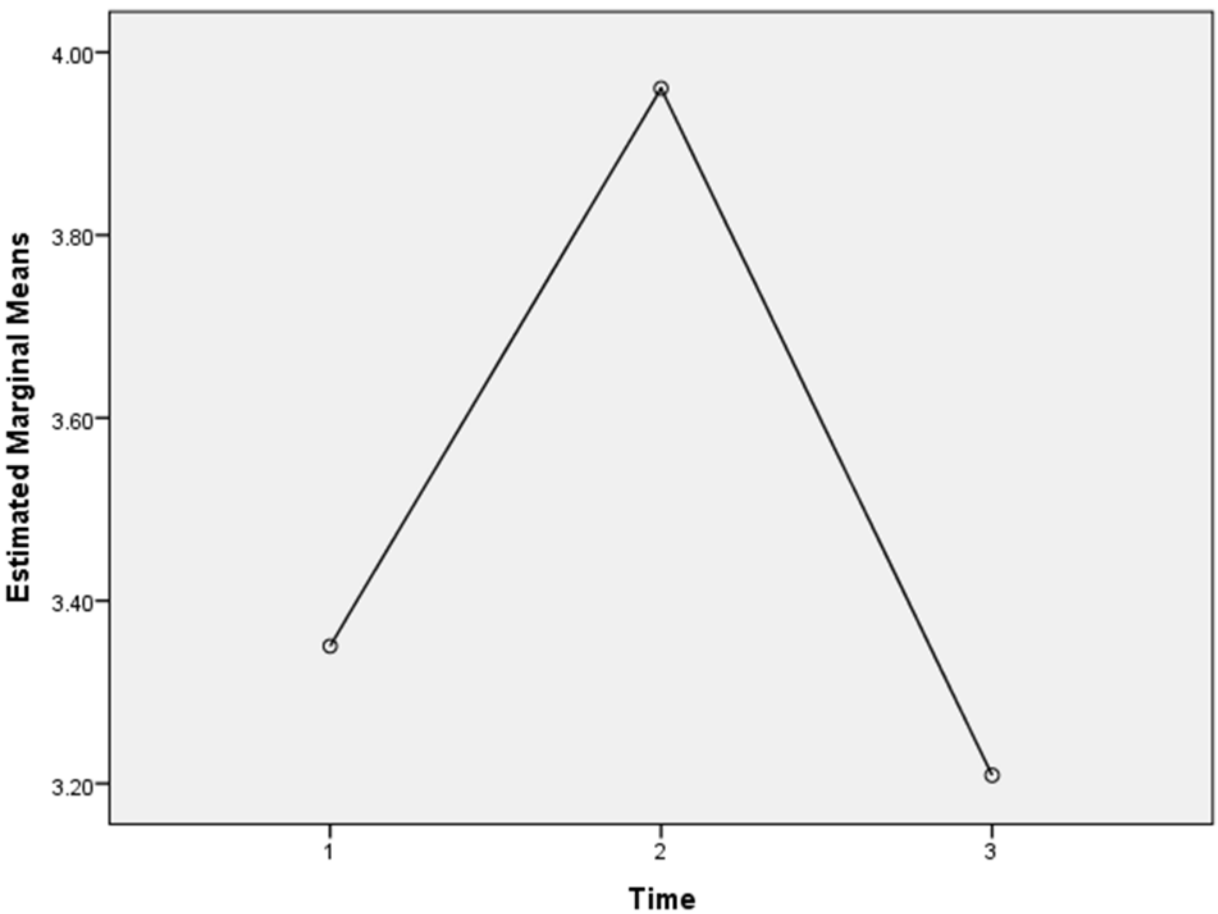

Figure 14: Change of Integrative Learning Dimension 5: Develop a professional digital identity

Discussion

This research makes a contribution not only to our understanding of how we can structure programs to enhance student achievement but also by building theory that explains how students learn. Regarding the potential applied contribution, this research aimed to explore the impact of an educational process designed to help students identify their knowledge, skills, and values so that they can connect and apply what they have learned to new situations, both as students and beyond. Overall, these results provide very encouraging evidence in support of an intervention that helps students foster integrative learning. Students who engage in the MPortfolio process, on average, experience significant learning gains across all five dimensions of integrative learning. Each dimension had a small to moderate effect size. Notably, the largest effect size related to students' abilities to provide evidence of their knowledge, skills, and values to others. Additionally, for four of these five dimensions, students, on average, maintained these significant gains two years after their MPortfolio experience. Not only do students learn through this process, the learning stays with them over time.

The main limitation of this type of pre/post research design is that one cannot make causal claims about the impact of the program. In other words, it is plausible that the changes that students experience are no different from the changes that they would have experienced anyway, if they had not gone through this process. The delayed treatment, control group design employed in this study addresses this limitation by eliminating selection bias in order to determine causality. The results of this research provide evidence of significant, positive effects with fairly large effect sizes for all five dimensions of integrative learning. The vast majority of research on the relationship between assessment and student achievement uses designs that allow researchers to establish correlations but not to make causal claims about this relationship. The use of this research design coupled with the significant findings in support of the program suggest that this study could have a demonstrable impact on our understanding of both theory and practice related to both assessment and student learning.

Regarding the potential theoretical contribution, the outcome of the research, integrative learning, has been recognized as an essential learning goal for 21st century higher education. Given its importance as a student outcome, there has been relatively little empirical research and theory building on integrative learning. This research expands the AAC&U's existing definition of integrative learning by incorporating a relational aspect that recognizes that individuals' learning experiences are inextricable from their social identities and interactions with others. The Integrative Learning Self-Assessment, the instrument employed in this research, reflects this relational aspect of integrative learning and asks students to reflect on the ways they integrate their learning in a far more detailed ways than the instruments employed in other studies that explore integrative learning. Additionally, the study breaks new ground by establishing a causal link between this construct of integrative learning and the reflective ePortfolio process. There is a great need for research that deeply explores how students learn by reflecting upon and integrating their disparate learning experiences and this study is a positive step as we develop our understanding of this topic.

In thinking about future directions for this research, it is important to acknowledge some of the limitations of the current study. One issue with the study is its reliance on self-reported levels of achievement of student outcomes. Historically, self-reported gains have been used extensively in research in postsecondary education. However, recent research calls into question the validity of self-reported measures. Porter (2011) analyzed the literature on this topic and concluded that students' self-reported measurements of their own experiences and the outcomes of their college experience fail to meet basic standards for validity and reliability. Other studies have reported mixed support for the validity of student self-reported measures. Anaya (1999) found that student-reported cognitive growth had modest relative validity, while studies conducted by Bowman (2010) and Gosen and Washbush (1999) indicate that self-reported gains had low correlations with direct measures of longitudinal change. While this is a potential limitation of the existing research, self-reported measures have been made essential contributions not only to higher education research but also to a much broader sphere of social science research. Pascarella (2001) and Pike (1995) urge institutions and researchers to exercise caution when using self-reported data and caution seems to be the most appropriate approach for carrying out the present study.

Similarly, the use of self-reported data introduces the issue of ceiling effects. The mean pre-survey values are particularly high for multiple dimensions of integrative learning. For example, the mean pre-survey value for Dimension 3: Recognize and adapt to differences in order to create solutions is 4.427, on a five-point scale. This is problematic for two reasons. First, from a statistical perspective, there is a cutoff in the distribution at the upper limit. This can lead to violations of the normality assumption and reported values at the upper limit may not be valid representations of the construct being measured. Second, for practical reasons, having such high pre-survey mean values when measuring student change leaves very little room for student improvement. It is encouraging that, despite the high pre-survey values, there were significant gains.

In order to address the issues of self-reported data and ceiling effects, a future direction for this research should be the analysis of ePortfolio content. As a tool for making learning visible, the ePortfolios include a wealth of information about student experiences, their reflections on these experiences, and their learning through the process. Analyzing this content can both validate self-reported responses and provide a much richer interpretation of students' experiences with and learning as a result of the MPortfolio process.

Finally, there is another future direction for this research that I have pursued but falls outside the already vast scope of the current study. This direction is to explore the differences between students who go through the MPortfolio process to identify sources of variation in student development. Ideally, this process will affect students equally, regardless of demographic characteristics, academic abilities, and co-curricular experiences. However, this may not be the case and it is important to determine what differences may exist. Additionally, to evaluate the strengths of the process, it is helpful to determine what learning process characteristics are associated with the largest gains. For example, do students in small groups fare better than those in large groups? Does the method of facilitation result in variation in integrative learning gains? Does it matter whether students engage in this process during the fall term or the winter term? Answering all of these questions can provide insight into how best to engage students in this reflective learning process.

Conclusion

The goal of this research is to increase our understanding about how students integrate their learning and whether educators can facilitate this process through the use of reflective ePortfolios. As this is the intersection of two emerging topics (integrative learning and ePortfolios), there is an opportunity to contribute to theory and practice in both of these areas. This research has implications for educators developing academic and co-curricular programs with integrative learning as an intended learning outcome. The present study provides evidence that the use of reflective ePortfolios results in significant learning gains for each dimension of integrative learning. Additionally, these learning gains persist years beyond the initial reflective ePortfolio experience. By recognizing that it is possible to facilitate integrative learning and understanding the ways in which we can best manage this process, educators can construct interventions that will enable students to make meaningful connections of their experiences, synthesize their learning, and gain a greater understanding of how their skills and knowledge can help them achieve their academic, professional, and personal goals.

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NO PLACE LIKE HOME? LOCATION IN MATRICULATION DECISIONS

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Abstract

Respondents to a recent survey of law school applicants indicated that school location was the single most important consideration in deciding where to apply (Law School Admission Council, 2012). Using unique Law School Admission Council data sources for matriculants to law school from fall 2008 through fall 2013 ($N = 260{,}564$), we utilized logistic regression to compute the likelihood of students' staying within their state of permanent residence. We also employed linear and multilevel regression to predict the continuous variable of distance traveled between student's home and law school. Results show that a majority of students (about 54%) remain in their state of permanent residence for law school, and this number has increased slightly over the time period to 56%. The median distance matriculants travel for law school is 102 miles. Analyses reveal statistically significant differences in likelihood to remain in state/distance traveled for law school by race/ethnicity, gender, lesbian/gay/bisexual/transgender (LGBT) status, average Law School Admission Test (LSAT) score, number of years between start of undergraduate college and enrolling in law school, number of applications submitted, number of law school acceptances, public/private undergraduate school, top undergraduate

school, initial undergraduate at a 2-year (community college) or 4-year college, fall semester enrolled (2005–2013), and law school tuition. Implications of this research are discussed.

Introduction

A limited number of previously published studies on undergraduate enrollment indicate that location plays a primary role in where college students decide to apply and ultimately matriculate. Some of these published studies have examined how far students travel to attend college. Work by Pryor et al. (2005) found that first-generation college students were more likely to attend schools closer to home. Two years later, Pryor et al. (2007) reported that the percentage of students attending college within 50 miles of their home did not change dramatically between 1969 and 2006 and that there were only slight differences between male and female students in the percentage of those who stayed within 50 miles of home.

A study conducted by Postsecondary Education Opportunity (1996) found that father's level of education and parental income were both positively related to how far students traveled to attend college. Mattern and Wyatt (2009) expanded on this research, examining the relationship between the attending institution's distance from home (based on zip codes) and ethnicity, parental education and income, high school GPA, and SAT scores. Their findings indicate that students with higher academic credentials (GPA and SAT) were more likely to travel farther to college. They also found a positive correlation between college distance from home and parent's level of education and income.

In the fall of 2012, the Law School Admission Council (LSAC) conducted a survey of law school applicants. Results of this survey indicate that law school location is the most important factor that students consider in selecting where to apply. This paper seeks to determine whether patterns that have been identified in studies of undergraduate students also apply to students seeking post-graduate training in law.

This paper examines the distance traveled from home for students attending law school to determine whether patterns are similar to studies of undergraduate students. Using unique LSAC data sources, we utilized logistic regression analyses to predict whether a student remained in state for law school, while controlling for many relevant variables. Additional analyses used logistic regression and multilevel modeling to determine average distances students travel to law school and whether there are differences by population subgroups.

Method

Sample

LSAC administers the Law School Admission Test (LSAT) and maintains data on students who take the test. In addition to determining test scores, LSAC tracks applications, admission, and matriculation for each candidate who applies to a law school approved by the American Bar Association (ABA). The analyses described below were conducted on data from 260,564 law school matriculants who began their academic year in fall 2008 through fall 2013.

Variables

Logistic regression and linear regression design controls for many relevant variables while determining the impact of multiple personal predictor variables, including race/ethnicity, gender, LGBT status, interactions between race/ethnicity and gender and between LGBT status and gender, college GPA, average LSAT score, number of years between start of undergraduate college and enrollment in law school, number of applications submitted, number of law school acceptances, and percentage of law school applications submitted in state and within region[1] (a

[1] Regional breakdowns are as follows: Far West—California, Hawaii, Nevada; Great Lakes—Illinois, Indiana, Michigan, Minnesota, Ohio, Wisconsin; Midsouth—Delaware, Kentucky, Maryland, North Carolina, Tennessee,

proxy for the importance to a student of staying close to home). Characteristics of the student's undergraduate and law school were also used as predictor variables, including whether the student attended a public/private undergraduate school, whether the undergraduate institution was considered a top [2] college, whether the student started at a 2-year (community college) or 4-year college, the selectivity[3] of the law school at which enrolled, fall semester enrolled (2005–2013), and the law school tuition[4].

Within State: Logistic Regression

Logistic regression was initially performed with the intent of modeling what matriculant characteristics were associated with a student's staying in his or her state of permanent residence for law school. Univariate statistics including *t*-tests and basic one-independent-variable logistic regressions were first used to determine what variables were likely correlated with staying in state for law school. While most basic *t*-tests were significant due to large sample size, we will discuss in the Results section those variables we consider to be practically significant. All analyses were conducted using the Statistical Analysis System (SAS) software.

We then used these results to construct a number of logistic models to identify predictor variables associated with attending law school in state or out of state. In all models, the following variables were included, as they were considered theoretically important and significant in most

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Virginia, Washington, DC, West Virginia; Midwest—Iowa, Kansas, Missouri, Nebraska, North Dakota, South Dakota; Mountain West—Arizona, Colorado, Idaho, Montana, New Mexico, Utah, Wyoming; New England—Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont; Northeast—New Jersey, New York, Pennsylvania; Northwest—Alaska, Oregon, Washington; South Central—Arkansas, Louisiana, Oklahoma, Texas; Southeast—Alabama, Florida, Georgia, Mississippi, South Carolina.

[2] Top colleges are considered the traditional Ivy League institutions: Brown University, Columbia University, Cornell University, Dartmouth College, Harvard University, Princeton University, University of Pennsylvania, and Yale University.

[3] Law school selectivity was calculated by taking the median of the sum of normalized college GPAs and average LSAT scores for each law school's first-year entering class.

[4] The law school tuition variable for private law schools was the total cost of full-time law school attendance, as the majority of matriculants were full-time. Public law school tuition was the total cost of either in- or out-of-state tuition, depending the candidate's state of permanent residence. Tuition data were retrieved from the American Bar Association (2013).

models: race/ethnicity, gender, LGBT status, number of years between start of undergraduate college and enrolling in law school, number of applications submitted, average LSAT score, public/private college, initial education at 2- or 4-year college, top college, fall semester (2005–2013), and law school tuition. The −2 Log Likelihood (−2LL) statistic was used to find the best combination of other predictors that may or may not improve the model. Table 1 illustrates this process.

Table 1
Fit Statistics for Logistic Regression Models Predicting Enrollment in In-State Law School

Added Independent Variables	−2 Log Likelihood	*N*	*df*
(No Additional Variables)	312,453.93	226,014	15
Count of Law Schools in Permanent State	311,917.27	225,660	16
Count of Law Schools in Permanent State & Percentage of Law Schools Applied in State	311,917.27	225,660	17

Note. Model with the independent variable Count of Law Schools in Permanent State (Model 2) yields the lowest −2LL with the simplest design. All models contained the following variables: race/ethnicity, gender, LGBT status, number of years between start of undergraduate college and enrolling in law school, number of applications submitted, average LSAT score, public/private college, initial education at 2- or 4-year college, top college, fall semester (2005–2013), and law school tuition.

First, the number of law schools in each student's home state was added to the model as a covariate to control for the available number of in-state alternatives. This addition led to a reduction in the −2LL value, and thus improved the model. The next model added the percentage of applications that a student submitted to in-state schools out of the total number of applications he or she submitted. For example, if a student applied to four schools in her home state, and one school outside her state, the variable would be 80% for that student. This variable is a proxy for a student's preference to remain close to home. While this variable was statistically significant (which is unsurprising, considering the large sample size), its addition did not lead to a reduction in −2LL. The optimal model used to interpret results then is the second model attempted, which included the number of law schools in permanent state as a covariate. The effects of the independent variables in this model on the likelihood of students' remaining in state for law school are discussed in the Results section.

Distance Traveled: Linear Regression and Multilevel Modeling

Linear regressions and multilevel modeling were next used to determine what best predicts how far a student travels for law school. The distance between a student's home zip code and the zip code for the law school he/she attended was calculated using the "zipcitydistance" function in SAS (SAS, 2014). Descriptive statistics and basic first-order correlations were computed to decide which independent variables to include in the model. These basic statistics can be found in the Results section.

Basic linear regressions were initially used to model the outcome of distance traveled to law school. We included race/ethnicity, gender, and LGBT status in all linear models. The first linear regression included these demographic characteristics, as well as the percentage of law schools the student applied to in region (a proxy for the importance of remaining in region), the number of schools to which the candidate was accepted, average LSAT score, selectivity of the law school to which he or she matriculated, tuition of that law school, fall semester enrolled, and count of law schools in candidate's state of permanent residence. This model results in an adjusted R-square value of 0.2354. The variance inflation factor (VIF) for average LSAT and selectivity of the law school was 2.9, indicating a problem with collinearity between these two independent variables. Because average LSAT score is considered an important predictor of a candidate's success in law school, we retained this variable and dropped law school selectivity. Rerunning the regression with the remaining variables resulted in an adjusted R-square value of

0.2352. The variables in this model account for about 24% of the variation in the distance a candidate travels for law school. Parameter estimates for the predictor variables in this model are discussed in the Results section.

The last set of models we ran were multilevel models to account for potential clustering effects in the data. We reasoned that candidates who enrolled in law school during the same fall semester, enrolled at the same law school, or were from the same state of permanent residence might tend to have more similar characteristics. Using the same independent variables that we had used in the linear regression models, we first modeled distance traveled to attend law school by grouping students according to fall semester, resulting in a –2LL fit statistic of 3,668,861. We then compared this model to a multilevel model in which we allowed the candidates to be grouped according to the law school of matriculation, which resulted in a better –2LL of 3,654,098. Finally, we allowed candidates to be grouped according to their state of permanent residence, as students from the same state may have more variance in common than students from different states. The –2LL for this model was 3,646,165. Therefore, the model with the lowest –2LL occurred when we grouped candidates according to their state of permanent residence. The results from this model are interpreted in the Results section. See Table 2 for the –2LL comparisons among models.

Table 2
Fit Statistics for Multilevel Models Predicting Distance Traveled to Attend Law School

Nested Variable	–2 Log Likelihood
Fall	3,668,861
Law School	3,654,098
Permanent State	3,646,165

Note. N = 237,227. Model with the nested variable Permanent State (Model 3) yields the lowest −2LL.

Results

Within State: Logistic Regression

Table 3 displays values for descriptive statistics (averages and percentages) that showed practically significant differences between students who stayed in state and those who went to out-of-state law schools.

Table 3

Student Characteristics by whether Student Remained in State for Law School

Student Characteristics	Stayed In State	Traveled Out of State
Average LSAT	155	157
Number of Applications Submitted	6.8	10.3
Years between Start of College and Enrolling in Law School	7.6	6.7
Started at 2-year College	60%	40%
Started at 4-year College	53%	47%
Graduated from a Public College	59%	41%
Graduated from a Private College	47%	53%
Graduated from a Top College	33%	66%
Average Law School Tuition	$31,412	$39,271
Average Selectivity Index*	0.13	0.29
Percentage of Applications Sent to In-State LS	64%	17%

As the table shows, students who stayed in state had lower average LSAT scores, applied to fewer schools, and waited slightly longer between graduation and law school enrollment. Students who began their education at 2-year college were 1.4 times more likely to stay in state for law school than students who started at 4-year institutions. Graduating from a public college is also associated with staying in state for law school: Students from public colleges were 1.6 times more likely than those who attended private colleges to stay in state for law school. Students attending a top[2] college were less likely to remain in state than other students. On average, students who remain in state for law school pay lower tuition[4], and generally go to a less selective[3] law school. Finally, the greater the percentage of in-state applications, the more likely a student is to go to an in-state law school. As Table 4 shows, LGBT students were less likely to stay in state than non-LGBT students.

Table 4

Percentage of Students Staying In State versus Traveling Out of State by LGBT Status

LGBT Status	*n*	Stayed In State	Traveled Out of State
LGBT	6,618	48%	52%
Not LGBT	253,130	55%	45%

Table 5 displays percentages of students staying in state versus traveling out of state by race/ethnicity. Black/African American students were least likely to stay in state. Hispanic students were most likely to stay in state (1.3 times more likely than others).

Table 5

Percentage of Students Staying In State Versus Traveling Out of State by Race/Ethnicity

Student Race/Ethnicity	*N*	Stayed In State	Traveled Out of State
Black/African American	20,109	45%	55%
White/Caucasian	173,667	55%	45%
Hispanic/Latino	18,124	61%	39%
Asian/Pacific Islander	18,500	52%	48%
American Indian/Alaska Native	1,432	55%	45%
All	260,564	54%	46%

The logistic model that best represented our data (as determined in the Methods section) was the model that included the count of law schools in students' permanent states. The parameter estimates and odds ratios for this model can be found in Table 6. With the large sample size, nearly all the parameters are statistically significant, with the exception of Asian/Pacific Islander (PI) and American Indian/Alaska Native. Notable results indicate that controlling for everything in the model, Black/African American matriculants are 0.5 as likely to remain in state as others. Also, for an increase of 1 year in the fall semester (e.g., for an increase from 2008 to 2009, or from 2009 to 2010), matriculants are 1.2 times more likely to remain in state.

Table 6

Parameter Estimates and Odds Ratios (Maximum Likelihood Estimates) for Logistic Regression Modeling Whether a Student will Remain In State

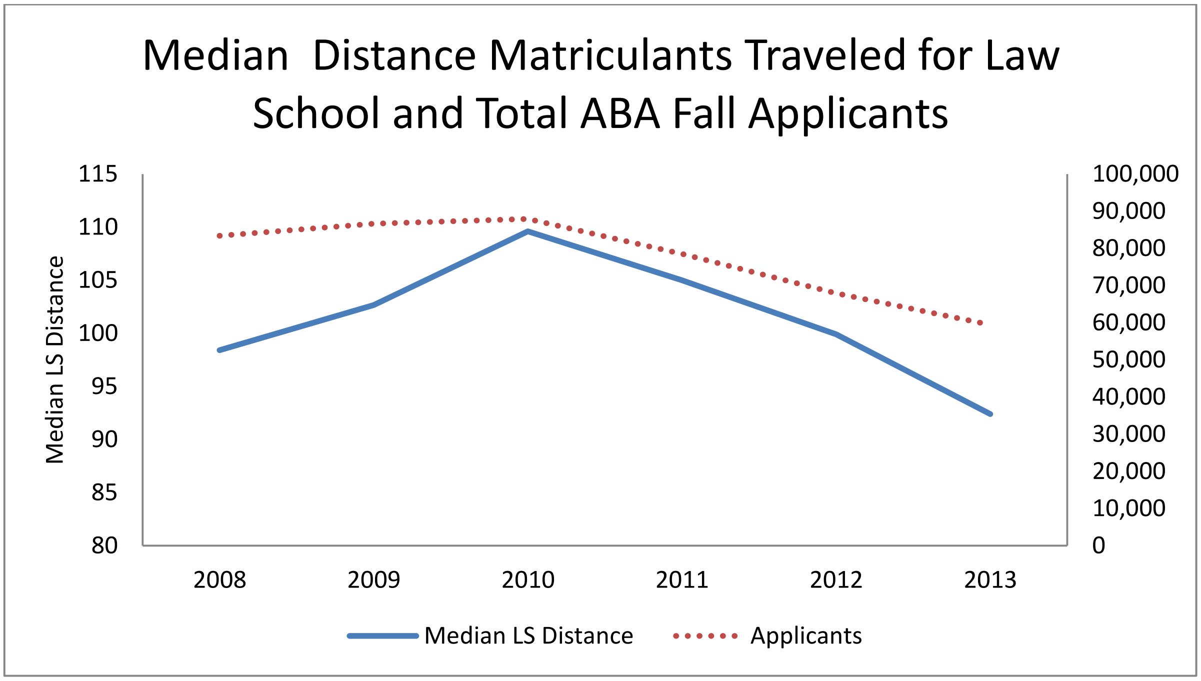
Parameter	Estimate	*SE*	Wald χ^2	$p > \chi^2$	Point Estimate	95% Wald CI	
Intercept	–432.1	6.6397	4234.8961	<.0001			
Years between starting college and law school	–0.00570	0.00128	19.6872	<.0001	0.994	0.992	0.997
# of applications submitted	–0.0766	0.000872	7721.5624	<.0001	0.926	0.925	0.928
Average LSAT score	0.0138	0.000740	345.7307	<.0001	1.014	1.012	1.015
Public college	0.0849	0.0107	62.7318	<.0001	1.089	1.066	1.112
Started at a 2-year college	–0.0483	0.0131	13.5233	0.0002	0.953	0.929	0.978
Top college	–0.0815	0.0278	8.6267	0.0033	0.922	0.873	0.973
Fall enrolled in law school	0.2158	0.00330	4283.9991	<.0001	1.241	1.233	1.249
# of law schools in home state	0.1319	0.000928	20181.1298	<.0001	1.141	1.139	1.143
Law school tuition	–0.00012	0.0000007	29872.5481	<.0001	1	1	1
Black/African American	–0.6815	0.0251	737.4078	<.0001	0.506	0.482	0.531
White/Caucasian	0.0331	0.0166	4.0058	0.0453	1.034	1.001	1.068
Hispanic/Latino	0.1218	0.0248	24.1033	<.0001	1.13	1.076	1.186
Asian/PI	0.0227	0.0246	0.8474	0.3573	1.023	0.975	1.074
American Indian/Alaska Native	–0.0964	0.0686	1.9732	0.1601	0.908	0.794	1.039
Female	0.0615	0.0101	37.1414	<.0001	1.063	1.043	1.085
LGBT	–0.1651	0.0321	26.3763	<.0001	0.848	0.796	0.903

Distance Traveled: Linear Regression and Multilevel Modeling

The overall average distance students go for law school is 384.74 miles; the median distance is 101.5, indicating distance traveled for law school is a positively skewed variable.

Over the time period observed, distance traveled for law school rose from a median distance of 98.4 in fall 2008 to 109.6 in fall 2010, then declined to a median value of 92.4 in fall 2013. Figure 1 illustrates this trend as it compares to the total number of ABA applicants applying to law school. As evident from the figure, the trends closely mimic each other.

Figure 1



Naturally, students differed in distance traveled for law school depending on their home state. A complete list of median miles traveled by state can be found in Table 7. Students from Alaska traveled the furthest median distance, with a median of 2,333 miles traveled for law school, followed by students from Utah (584 miles), Colorado (579), Idaho (337), and Montana (298). Students from Minnesota, Massachusetts, Maryland, New York, and Oklahoma traveled the least (24, 29, 36, 39, and 40 miles respectively).

Table 7

Median Distance in Miles Traveled for Law School by State of Permanent Residence

Permanent State	*n*	*Mdn*	Permanent State	*n*	*Mdn*
AK	385	2,333	DE	701	77
UT	3,091	584	OH	8,864	72
CO	3,694	579	CT	3,768	71
ID	891	337	IL	11,382	71
MT	771	298	MI	7,473	70
AZ	4,113	296	LA	3,880	62
NV	1,674	267	NJ	10,423	49
TN	3,584	225	RI	884	49
WA	4,939	222	NE	1,362	47
ND	501	215	OK	2,150	40
WY	366	209	NY	24,676	39
DC	2,824	202	MD	6,560	36
SD	554	201	MA	7,450	29
TX	18,083	195	MN	4,289	24
NM	1,135	191			
VT	447	180			
FL	19,835	160			
OR	2,253	145			
WI	3,708	141			
MS	1,642	138			
GA	7,609	134			
HI	961	131			
VA	8,091	128			
WV	1,134	127			
AL	2,522	125			
KS	1,980	125			
MO	4,106	119			
IA	1,955	118			
SC	3,028	115			
NC	6,903	110			
ME	818	110			
IN	4,075	101			
CA	33,109	87			
AR	1,622	87			
PA	10,460	85			
KY	2,976	84			
NH	863	80			

Distance traveled for law school was positively correlated with law school tuition[4] (0.25), the number of applications a student submitted (0.23), the selectivity[3] of the law school (0.20), the number of accepted applications (0.17), and average LSAT score (0.15).

Averages along important demographic and undergraduate characteristics were calculated, in addition to Cohen's d effect size (ES) using a SAS macro (Kadel & Kip, 2012). Cohen's d ES measures the standard magnitude of association between two variables (e.g., students indicating an LGBT status versus non-LGBT students), and is generally calculated as the mean difference between these two variables over a pooled measure of their standard deviation. We used this ES because of its base rate–insensitive nature, base rate being defined as the number of subjects in one variable group versus the other. As this ratio departs from 50/50, the generally used r correlation ES will be increasingly small, and will not reflect an effect observed in a very small sector of the population (McGrath & Meyer, 2006). As LGBT students comprise only 3% of law school matriculants, and many other important demographic groups we considered were a small segment of law school matriculants, Cohen's d ES was calculated to represent differences in distances traveled among various subgroups. While the literature varies on what is considered a large or small ES, .60 is often considering to be a large ES, .30 considered moderate, and .10 considered small (Synder & Lawson, 1993, p. 345).

Table 8 displays average distances traveled by groups of students based on race/ethnicity. Asian/PI matriculants were more likely to travel far distances than others, with a moderate ES. American Indian/Alaska Natives traveled a further distance than others, with a small ES. Hispanic matriculants are more likely than non-Hispanics to travel far distances, though with a very small ES. Black/African American matriculants travel a slightly higher average distance to law school than others, though again the ES is very small. White/Caucasian students are less likely than non-White/Caucasian matriculants to travel far distances for law school with a small to moderate ES. That Hispanic/Latino students are likely to travel far distances, but remain within their state, is an interesting finding. Perhaps this is due to large Hispanic/Latino populations in big states such as Texas, California, and Arizona, so that while many Hispanic/Latino students remain in state, they are still traveling large distances. Further research is needed to determine the truth of this hypothesis.

Table 8

Average Distance in Miles Traveled to Law School by Race/Ethnicity

Student Race/Ethnicity	*N*	*M*	ES
Asian/Pacific Islander	18,500	532	0.26
American Indian/Alaska Native	1,432	449	0.10
Hispanic/Latino	18,124	433	0.08
Black/African American	20,109	393	0.02
White/Caucasian	173,667	354	-0.15
All	260,564	385	

Female students traveled shorter distances than their male counterparts, though with only a small ES, as shown in Table 9.

Table 9

Average Distance in Miles Traveled to Law School by Gender

Gender	*N*	*M*	ES
Female	121,934	378	−.02
Male	137,457	389	

LGBT matriculants were more likely to travel far distances for law school, with a moderately large ES, as seen in Table 10.

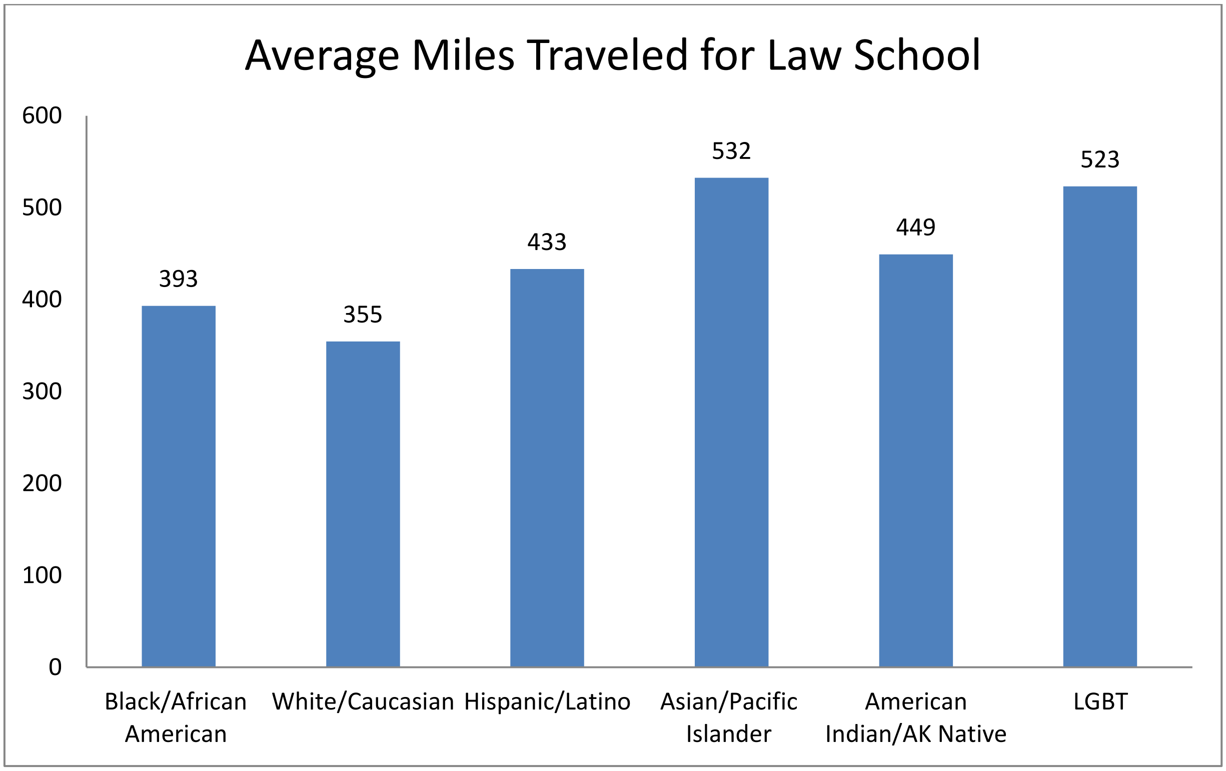
Table 10

Average Distance in Miles Traveled to Law School by LGBT Status

LGBT Status	*n*	*M*	ES
LGBT	6,618	523	.23
Non-LGBT	253,130	381	

Figure 2 displays the average miles traveled for law school by race/ethnicity and LGBT status. When interaction effects were tested between gender and race/ethnicity and between gender and LGBT status, female students were less likely to travel far distances in all of the categories, though ES was generally small.

Figure 2



Looking at the characteristics of undergraduate schools students attended in Table 11, students from public undergraduate college were less likely to travel far for college, though with a small ES. Attending a top[2] college indicates matriculants are more likely to travel farther for law school, with a moderate ES.

Table 11
Average Distance Traveled to Law School in Miles by Undergraduate Characteristics

Undergraduate Characteristic	*n*	*M*	ES
Public	149,198	365	−0.10
Non-Public	96,375	423	
Top College	9,475	565	0.30
Non-Top College	250,273	378	

The parameters for the linear regression model that best represented our data (as discussed in the Methods section) can be found in Table 12. This model explains 24% of the variation in distance traveled to law school, as indicated by the 0.2352 R-square. The model indicates that for an increase in 1% of the percentage of law schools applied to in region, a student is likely to stay about 8 miles closer to home, all other variables held constant. Number of acceptances is negatively related to distance in our model, though a simple correlation indicated a positive relationship to distance, albeit a fairly small correlation of 0.17. Also in the model, being Black/African American indicates a likelihood of staying about 13 miles closer to home, which is likewise different from the previously discussed indicators that generally indicated Black/African American students were slightly more likely to travel further, though with a very small ES of 0.02. Because of the small correlation and ES in these variables, and because in the model many variables are held constant, the shift in sign in both number of acceptances and Black/African American is not particularly surprising. Average LSAT remains positively associated with distance, as does law school tuition. Because law school tuition is measured in dollars, an increase in every $1,000 of tuition can be interpreted to indicate that the student will go to law school an additional 7.1 miles further, holding the other variables constant. Also positively related to distance is the number of law schools in the student's home state, as well as being Hispanic/Latino, Asian/PI, American Indian/Alaska Native, and LGBT. Fall semester, as well as being Black/African American, White/Caucasian, and Female, are negatively associated with law school distance. All parameter estimates are statistically significant.

Table 12
Parameter Estimates for Linear Regression Modeling Distance Traveled for Law School

Variable	Parameter Estimate	*SE*	*t* Value	*p* > |t|	CI	
Intercept	24,873	1462.98	17	<.0001	22,005	27,740
Percentage of law schools applied to within region	–8.05231	0.03768	–213.7	<.0001	–8.1262	–7.9785
# of acceptances	–4.91368	0.4103	–11.98	<.0001	–5.7179	–4.1095
Average LSAT	0.44939	0.16923	2.66	0.0079	0.11769	0.78108
LS tuition	0.00709	0.00013	55.27	<.0001	0.00684	0.00734
Fall	–12.141	0.72612	–16.72	<.0001	–13.564	–10.718
# of law schools in home state	10.49765	0.19919	52.7	<.0001	10.1072	10.8881
Black/African American	–12.591	5.57782	–2.26	0.024	–23.523	–1.6586
White/Caucasian	–37.0262	3.75832	–9.85	<.0001	–44.392	–29.66
Hispanic/Latino	28.0935	5.59477	5.02	<.0001	17.1279	39.0591
Asian/PI	47.07938	5.51827	8.53	<.0001	36.2637	57.895
American Indian/AK Native	77.6163	15.6402	4.96	<.0001	46.9619	108.271
Female	–8.71981	2.29642	–3.8	0.0001	–13.221	–4.2189
LGBT	58.86951	7.18041	8.2	<.0001	44.7961	72.9429

Note. df=1 for each variable.

The final model on which we reported results was a multilevel model that nested students by their state of permanent residence. The parameters can be found in Table 13. The number of law schools in the student's home state, as well as the many races/ethnicities including White/Caucasian, Hispanic/Latino, Asian/PI, and American Indian/Alaska Native are no longer statistically significant once we consider students as nested within their home state. Black/African American is here positively associated with distance. Number of acceptances is again negatively associated with distance as in the linear model, and this time average LSAT score is slightly negatively associated with distance traveled.

Table 13

Parameter Estimates for Multilevel Model (Students Nested Within Home State) Predicting Distance Traveled for Law School

Effect	Estimate	*SE*	*df*	*t* Value	*p* > |t|
Intercept	37,642	1410.52	49	26.69	<.0001
Percent of law schools applied within region	–7.6995	0.03683	240,000	–209.05	<.0001
# of acceptances	–4.0101	0.3919	240,000	–10.23	<.0001
Average LSAT	–0.5284	0.1624	240,000	–3.25	0.0011
LS tuition	0.0103	0.000133	240,000	77.43	<.0001
Fall	–18.429	0.6998	240,000	–26.34	<.0001
# of law schools in home state	–5.7186	8.8102	240,000	–0.65	0.5163
Black/African American	38.4741	5.3665	240,000	7.17	<.0001
White/Caucasian	–5.782	3.5941	240,000	–1.61	0.1077
Hispanic/Latino	5.9251	5.3918	240,000	1.1	0.2718
Asian/PI	7.0248	5.278	240,000	1.33	0.1832
American Indian/Alaska Native	28.2679	15.0191	240,000	1.88	0.0598
Female	–10.0088	2.1915	240,000	–4.57	<.0001
LGBT	45.0693	6.8451	240,000	6.58	<.0001

Discussion

With a wealth of data at its disposal, LSAC is in a unique position to research patterns of application and matriculation behaviors in higher education. Below, we will discuss the main areas of investigation using the main analytical subgroups of within-state analyses and distance traveled analyses.

Within State Analyses and Limitations. Given the increasingly difficult market pressures targeting law schools and higher education in general, we theorized that some potential law school students would be enticed to matriculate at their in-state institutions because of perceptions of cost savings, or because of the desire to stay near home. We further theorized that this effect may be greater for some subpopulations. Ultimately, we found that many factors played a role in the decision to enroll at a law school within state versus out of state. Confirming our theories, applicants who attended 2-year (community) colleges and public universities were more likely to select an institution in state, whereas graduates from top undergraduate institutions were more likely to leave their state for law school.

We were not particularly surprised by our identity group analyses, which showed that Black/African American matriculants were least likely among all ethnic groups to stay in state. Similarly, the fact that Hispanic/Latino matriculants most often stayed in state confirmed our hypotheses. Likewise, we had hypothesized that LGBT students may be more willing to leave their respective states, perhaps for specialized law programs or to live in more socially progressive areas, but we were astonished by the large magnitude of the effect. Among all our subgroups, LGBT applicants were the most likely to leave their home state for law school. Keeping in mind that there was notable variation within the LGBT group in terms of gender, ethnicity, and age, the fact that these matriculants most often left their respective states is a noteworthy effect. Now that we are aware of the effect, we intend to pursue this topic further. One limitation of the within-state analyses is that there are states that have larger cities situated near their borders. Thus, applicants may matriculate at a law school that is technically out of state, but one that is nevertheless located nearby. An example of this issue would be New Jersey residents traveling with relative ease into Philadelphia or New York City metro area law schools.

Distance Traveled Analyses and Limitations. Distance traveled proved a rather complicated variable to address effectively, but one we thought important to include in our research, partly to address the limitations of the parsimonious, but restrictive, state-level analyses. Unsurprisingly, being so far from the mainland of the U.S. and having no law school of its own, Alaskan residents traveled the farthest. More surprising were states such as Minnesota, Massachusetts, and Oklahoma, which had the smallest median distances traveled. The explanation for this outcome is unclear, but we hope to investigate further. Among ethnic groups, Black/African American, Hispanic/Latino, and American Indian/Alaskan Native matriculants were more likely to travel somewhat longer distances for law school, but the effect sizes were small. White/Caucasian matriculants tended to travel shorter distances compared to their non-White/Caucasian peers. The significant effect of distances traveled for Black/African American matriculants supports results found in the literature. With the largest total effect size, however, Asian/Pacific Islander matriculants traveled farther than non-Asian/Pacific Islanders, which is opposite the outcome reported in the existing literature. Switching from the linear model to the multilevel model, many ethnic effects were no longer significant, except for Black/African American matriculants. We were hoping to confirm our linear analysis in the multilevel model, but clearly a complex effect is occurring, which we will pursue in future research.

Regardless of ethnic group affiliation, female matriculants traveled very slightly shorter distances than their male counterparts, but with only a small effect size. It seems this effect is quite small and deserves additional research to clarify whether the effect is too small to be of practical significance. Of notable significance was LGBT matriculants, with the second largest effect size for traveling farther than non-LGBT matriculants, with an average distance of over 500 miles. Obviously, this surprising outcome deserves further analysis. For undergraduate university factors, matriculants attending a public undergraduate institution were less likely to travel far for law school, whereas attending a top undergraduate institution is associated with traveling greater distances for law school. Presumably, graduates from top institutions are more competitive and seek to matriculate at highly selective law schools, thus making them willing to travel farther to reach that goal.

Given our massive sample sizes and our large amount of demographic data, we thought that this distance analysis would be useful to both researchers and admission officers. These results, however, were not without their limitations. One problem we encountered was the data distributions. Some skewness within subpopulations often occurs, and our data were no exception. Skewness can bias analyses so that effects are artificially exaggerated or minimized. Data transformations, such as a log transformation, may yield more accurate results. In addition, our results for both sets of analyses may not be fully generalizable outside of the law school applicant population. Our goal is to present enough information for researchers to use this method to examine their own databases or perhaps other large-scale databases such as Higher Education Research Institute (HERI) or federal education data.

Conclusions and Future Directions

Our research confirms much of the prior research but also complicates it, making a case for targeting admission marketing based on subgroup information. While our current results cannot yet suggest specific admission marketing recommendations, we hope to be able to provide more specific information by expanding our research in the future. We plan to accomplish these refinements by addressing the methods, analyses, and databases. For the methods and analyses, we hope to refine our analytical model and determine how the unexplained differences between the in-state model and the distance model work. From there, we can further refine our model and perhaps create structural equation models or hierarchical linear models to better clarify our outcomes. It may be useful, for example, to examine whether or not matriculants choose regions but not necessarily states. As we have created our current models, it is unclear whether there are moderator or mediator effects that we omitted but that could improve our models and explanations. Lastly, given our large datasets and the lack of consistency of some results, we may want to use explore data reduction techniques such as factor analysis or cluster analysis.

Further, we hope to combine our data with the data available from the HERI Cooperative Institutional Research Program (CIRP) so that we can delve further into the longitudinal aspects of student choice in selecting a law school. Previous research on distance traveled for higher education found a notable impact for variables such as parental education and income. By merging our data with HERI-CIRP data, we would be able to further elucidate student institutional choice behaviors. In addition, we would like to investigate metro areas as separate location variables that could be attractive to potential matriculants. We theorize that some students would choose metro areas because of employment, internship, or personal opportunities that may not be available elsewhere. Finally, we hope to expand these results to include measurable results, such as examining the impact of distance traveled on first-year performance in law school.

In this paper, we discussed in-state behaviors as well as overall distance traveled to attend law school. Our goal was to assist researchers and admission officers in targeting students for marketing purposes, and we revealed some of the differences within the subpopulations of law school matriculants. Our hope in this research project was to create a summary of matriculants' willingness to travel to a law school by using varied analytical techniques. Future research will both broaden and deepen our current strategy with the goal of ultimately achieving a fuller understanding of essential admission issues and applicant matriculation behaviors.

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NO PLACE LIKE HOME? LOCATION IN MATRICULATION DECISIONS

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Abstract

Respondents to a recent survey of law school applicants indicated that school location was the single most important consideration in deciding where to apply (Law School Admission Council, 2012). Using unique Law School Admission Council data sources for matriculants to law school from fall 2008 through fall 2013 (N = 260,564), we utilized logistic regression to compute the likelihood of students' staying within their state of permanent residence. We also employed linear and multilevel regression to predict the continuous variable of distance traveled between student's home and law school. Results show that a majority of students (about 54%) remain in their state of permanent residence for law school, and this number has increased slightly over the time period to 56%. The median distance matriculants travel for law school is 102 miles. Analyses reveal statistically significant differences in likelihood to remain in state/distance traveled for law school by race/ethnicity, gender, lesbian/gay/bisexual/transgender (LGBT) status, average Law School Admission Test (LSAT) score, number of years between start of undergraduate college and enrolling in law school, number of applications submitted, number of law school acceptances, public/private undergraduate school, top undergraduate

school, initial undergraduate at a 2-year (community college) or 4-year college, fall semester enrolled (2005–2013), and law school tuition. Implications of this research are discussed.

Introduction

A limited number of previously published studies on undergraduate enrollment indicate that location plays a primary role in where college students decide to apply and ultimately matriculate. Some of these published studies have examined how far students travel to attend college. Work by Pryor et al. (2005) found that first-generation college students were more likely to attend schools closer to home. Two years later, Pryor et al. (2007) reported that the percentage of students attending college within 50 miles of their home did not change dramatically between 1969 and 2006 and that there were only slight differences between male and female students in the percentage of those who stayed within 50 miles of home.

A study conducted by Postsecondary Education Opportunity (1996) found that father's level of education and parental income were both positively related to how far students traveled to attend college. Mattern and Wyatt (2009) expanded on this research, examining the relationship between the attending institution's distance from home (based on zip codes) and ethnicity, parental education and income, high school GPA, and SAT scores. Their findings indicate that students with higher academic credentials (GPA and SAT) were more likely to travel farther to college. They also found a positive correlation between college distance from home and parent's level of education and income.

In the fall of 2012, the Law School Admission Council (LSAC) conducted a survey of law school applicants. Results of this survey indicate that law school location is the most important factor that students consider in selecting where to apply. This paper seeks to determine whether patterns that have been identified in studies of undergraduate students also apply to students seeking post-graduate training in law.

This paper examines the distance traveled from home for students attending law school to determine whether patterns are similar to studies of undergraduate students. Using unique LSAC data sources, we utilized logistic regression analyses to predict whether a student remained in state for law school, while controlling for many relevant variables. Additional analyses used logistic regression and multilevel modeling to determine average distances students travel to law school and whether there are differences by population subgroups.

Method

Sample

LSAC administers the Law School Admission Test (LSAT) and maintains data on students who take the test. In addition to determining test scores, LSAC tracks applications, admission, and matriculation for each candidate who applies to a law school approved by the American Bar Association (ABA). The analyses described below were conducted on data from 260,564 law school matriculants who began their academic year in fall 2008 through fall 2013.

Variables

Logistic regression and linear regression design controls for many relevant variables while determining the impact of multiple personal predictor variables, including race/ethnicity, gender, LGBT status, interactions between race/ethnicity and gender and between LGBT status and gender, college GPA, average LSAT score, number of years between start of undergraduate college and enrollment in law school, number of applications submitted, number of law school acceptances, and percentage of law school applications submitted in state and within region[1] (a

[1] Regional breakdowns are as follows: Far West—California, Hawaii, Nevada; Great Lakes—Illinois, Indiana, Michigan, Minnesota, Ohio, Wisconsin; Midsouth—Delaware, Kentucky, Maryland, North Carolina, Tennessee,

proxy for the importance to a student of staying close to home). Characteristics of the student's undergraduate and law school were also used as predictor variables, including whether the student attended a public/private undergraduate school, whether the undergraduate institution was considered a top [2] college, whether the student started at a 2-year (community college) or 4-year college, the selectivity[3] of the law school at which enrolled, fall semester enrolled (2005–2013), and the law school tuition[4].

Within State: Logistic Regression

Logistic regression was initially performed with the intent of modeling what matriculant characteristics were associated with a student's staying in his or her state of permanent residence for law school. Univariate statistics including *t*-tests and basic one-independent-variable logistic regressions were first used to determine what variables were likely correlated with staying in state for law school. While most basic *t*-tests were significant due to large sample size, we will discuss in the Results section those variables we consider to be practically significant. All analyses were conducted using the Statistical Analysis System (SAS) software.

We then used these results to construct a number of logistic models to identify predictor variables associated with attending law school in state or out of state. In all models, the following variables were included, as they were considered theoretically important and significant in most

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Virginia, Washington, DC, West Virginia; Midwest—Iowa, Kansas, Missouri, Nebraska, North Dakota, South Dakota; Mountain West—Arizona, Colorado, Idaho, Montana, New Mexico, Utah, Wyoming; New England—Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont; Northeast—New Jersey, New York, Pennsylvania; Northwest—Alaska, Oregon, Washington; South Central—Arkansas, Louisiana, Oklahoma, Texas; Southeast—Alabama, Florida, Georgia, Mississippi, South Carolina.

[2] Top colleges are considered the traditional Ivy League institutions: Brown University, Columbia University, Cornell University, Dartmouth College, Harvard University, Princeton University, University of Pennsylvania, and Yale University.

[3] Law school selectivity was calculated by taking the median of the sum of normalized college GPAs and average LSAT scores for each law school's first-year entering class.

[4] The law school tuition variable for private law schools was the total cost of full-time law school attendance, as the majority of matriculants were full-time. Public law school tuition was the total cost of either in- or out-of-state tuition, depending the candidate's state of permanent residence. Tuition data were retrieved from the American Bar Association (2013).

models: race/ethnicity, gender, LGBT status, number of years between start of undergraduate college and enrolling in law school, number of applications submitted, average LSAT score, public/private college, initial education at 2- or 4-year college, top college, fall semester (2005–2013), and law school tuition. The −2 Log Likelihood (−2LL) statistic was used to find the best combination of other predictors that may or may not improve the model. Table 1 illustrates this process.

Table 1
Fit Statistics for Logistic Regression Models Predicting Enrollment in In-State Law School

Added Independent Variables	−2 Log Likelihood	*N*	*df*
(No Additional Variables)	312,453.93	226,014	15
Count of Law Schools in Permanent State	311,917.27	225,660	16
Count of Law Schools in Permanent State & Percentage of Law Schools Applied in State	311,917.27	225,660	17

Note. Model with the independent variable Count of Law Schools in Permanent State (Model 2) yields the lowest −2LL with the simplest design. All models contained the following variables: race/ethnicity, gender, LGBT status, number of years between start of undergraduate college and enrolling in law school, number of applications submitted, average LSAT score, public/private college, initial education at 2- or 4-year college, top college, fall semester (2005–2013), and law school tuition.

First, the number of law schools in each student's home state was added to the model as a covariate to control for the available number of in-state alternatives. This addition led to a reduction in the −2LL value, and thus improved the model. The next model added the percentage of applications that a student submitted to in-state schools out of the total number of applications he or she submitted. For example, if a student applied to four schools in her home state, and one school outside her state, the variable would be 80% for that student. This variable is a proxy for a student's preference to remain close to home. While this variable was statistically significant (which is unsurprising, considering the large sample size), its addition did not lead to a reduction in −2LL. The optimal model used to interpret results then is the second model attempted, which included the number of law schools in permanent state as a covariate. The effects of the independent variables in this model on the likelihood of students' remaining in state for law school are discussed in the Results section.

Distance Traveled: Linear Regression and Multilevel Modeling

Linear regressions and multilevel modeling were next used to determine what best predicts how far a student travels for law school. The distance between a student's home zip code and the zip code for the law school he/she attended was calculated using the "zipcitydistance" function in SAS (SAS, 2014). Descriptive statistics and basic first-order correlations were computed to decide which independent variables to include in the model. These basic statistics can be found in the Results section.

Basic linear regressions were initially used to model the outcome of distance traveled to law school. We included race/ethnicity, gender, and LGBT status in all linear models. The first linear regression included these demographic characteristics, as well as the percentage of law schools the student applied to in region (a proxy for the importance of remaining in region), the number of schools to which the candidate was accepted, average LSAT score, selectivity of the law school to which he or she matriculated, tuition of that law school, fall semester enrolled, and count of law schools in candidate's state of permanent residence. This model results in an adjusted R-square value of 0.2354. The variance inflation factor (VIF) for average LSAT and selectivity of the law school was 2.9, indicating a problem with collinearity between these two independent variables. Because average LSAT score is considered an important predictor of a candidate's success in law school, we retained this variable and dropped law school selectivity. Rerunning the regression with the remaining variables resulted in an adjusted R-square value of

0.2352. The variables in this model account for about 24% of the variation in the distance a candidate travels for law school. Parameter estimates for the predictor variables in this model are discussed in the Results section.

The last set of models we ran were multilevel models to account for potential clustering effects in the data. We reasoned that candidates who enrolled in law school during the same fall semester, enrolled at the same law school, or were from the same state of permanent residence might tend to have more similar characteristics. Using the same independent variables that we had used in the linear regression models, we first modeled distance traveled to attend law school by grouping students according to fall semester, resulting in a –2LL fit statistic of 3,668,861. We then compared this model to a multilevel model in which we allowed the candidates to be grouped according to the law school of matriculation, which resulted in a better –2LL of 3,654,098. Finally, we allowed candidates to be grouped according to their state of permanent residence, as students from the same state may have more variance in common than students from different states. The –2LL for this model was 3,646,165. Therefore, the model with the lowest –2LL occurred when we grouped candidates according to their state of permanent residence. The results from this model are interpreted in the Results section. See Table 2 for the –2LL comparisons among models.

Table 2
Fit Statistics for Multilevel Models Predicting Distance Traveled to Attend Law School

Nested Variable	–2 Log Likelihood
Fall	3,668,861
Law School	3,654,098
Permanent State	3,646,165

Note. N = 237,227. Model with the nested variable Permanent State (Model 3) yields the lowest −2LL.

Results

Within State: Logistic Regression

Table 3 displays values for descriptive statistics (averages and percentages) that showed practically significant differences between students who stayed in state and those who went to out-of-state law schools.

Table 3

Student Characteristics by whether Student Remained in State for Law School

Student Characteristics	Stayed In State	Traveled Out of State
Average LSAT	155	157
Number of Applications Submitted	6.8	10.3
Years between Start of College and Enrolling in Law School	7.6	6.7
Started at 2-year College	60%	40%
Started at 4-year College	53%	47%
Graduated from a Public College	59%	41%
Graduated from a Private College	47%	53%
Graduated from a Top College	33%	66%
Average Law School Tuition	$31,412	$39,271
Average Selectivity Index*	0.13	0.29
Percentage of Applications Sent to In-State LS	64%	17%

As the table shows, students who stayed in state had lower average LSAT scores, applied to fewer schools, and waited slightly longer between graduation and law school enrollment. Students who began their education at 2-year college were 1.4 times more likely to stay in state for law school than students who started at 4-year institutions. Graduating from a public college is also associated with staying in state for law school: Students from public colleges were 1.6 times more likely than those who attended private colleges to stay in state for law school. Students attending a top[2] college were less likely to remain in state than other students. On average, students who remain in state for law school pay lower tuition[4], and generally go to a less selective[3] law school. Finally, the greater the percentage of in-state applications, the more likely a student is to go to an in-state law school. As Table 4 shows, LGBT students were less likely to stay in state than non-LGBT students.

Table 4
Percentage of Students Staying In State versus Traveling Out of State by LGBT Status

LGBT Status	*n*	Stayed In State	Traveled Out of State
LGBT	6,618	48%	52%
Not LGBT	253,130	55%	45%

Table 5 displays percentages of students staying in state versus traveling out of state by race/ethnicity. Black/African American students were least likely to stay in state. Hispanic students were most likely to stay in state (1.3 times more likely than others).

Table 5
Percentage of Students Staying In State Versus Traveling Out of State by Race/Ethnicity

Student Race/Ethnicity	*N*	Stayed In State	Traveled Out of State
Black/African American	20,109	45%	55%
White/Caucasian	173,667	55%	45%
Hispanic/Latino	18,124	61%	39%
Asian/Pacific Islander	18,500	52%	48%
American Indian/Alaska Native	1,432	55%	45%
All	260,564	54%	46%

The logistic model that best represented our data (as determined in the Methods section) was the model that included the count of law schools in students' permanent states. The parameter estimates and odds ratios for this model can be found in Table 6. With the large sample size, nearly all the parameters are statistically significant, with the exception of Asian/Pacific Islander (PI) and American Indian/Alaska Native. Notable results indicate that controlling for everything in the model, Black/African American matriculants are 0.5 as likely to remain in state as others. Also, for an increase of 1 year in the fall semester (e.g., for an increase from 2008 to 2009, or from 2009 to 2010), matriculants are 1.2 times more likely to remain in state.

Table 6

Parameter Estimates and Odds Ratios (Maximum Likelihood Estimates) for Logistic Regression Modeling Whether a Student will Remain In State

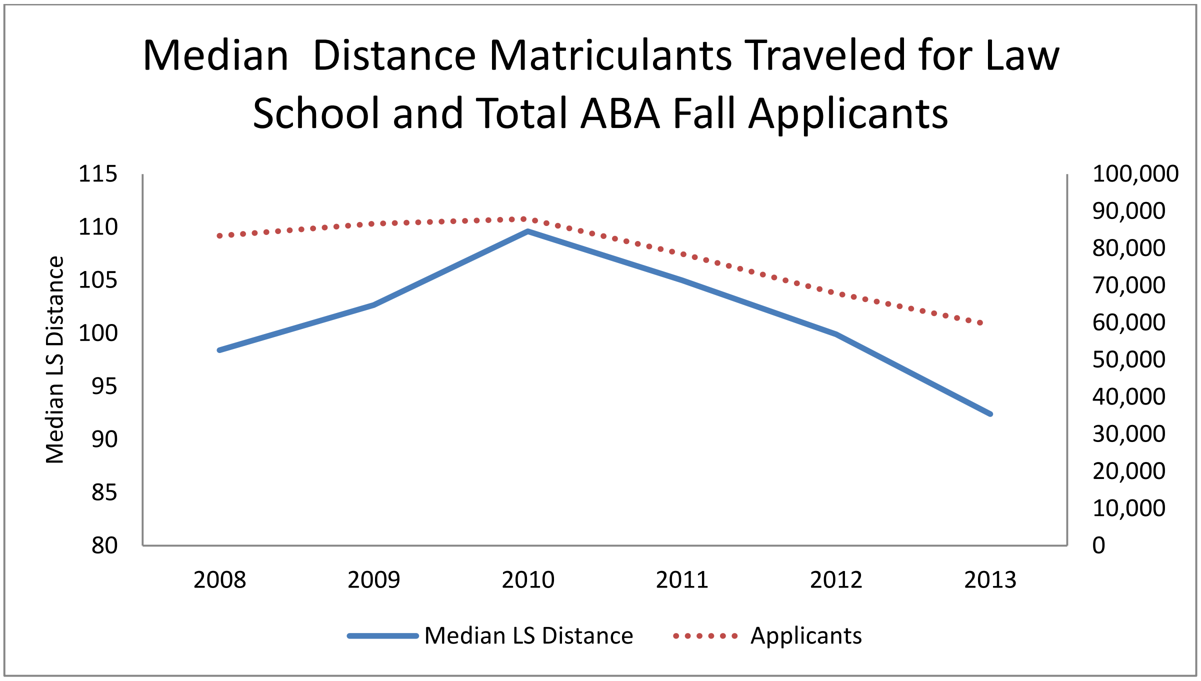
Parameter	Estimate	*SE*	Wald χ^2	$p > \chi^2$	Point Estimate	95% Wald CI	
Intercept	–432.1	6.6397	4234.8961	<.0001			
Years between starting college and law school	–0.00570	0.00128	19.6872	<.0001	0.994	0.992	0.997
# of applications submitted	–0.0766	0.000872	7721.5624	<.0001	0.926	0.925	0.928
Average LSAT score	0.0138	0.000740	345.7307	<.0001	1.014	1.012	1.015
Public college	0.0849	0.0107	62.7318	<.0001	1.089	1.066	1.112
Started at a 2-year college	–0.0483	0.0131	13.5233	0.0002	0.953	0.929	0.978
Top college	–0.0815	0.0278	8.6267	0.0033	0.922	0.873	0.973
Fall enrolled in law school	0.2158	0.00330	4283.9991	<.0001	1.241	1.233	1.249
# of law schools in home state	0.1319	0.000928	20181.1298	<.0001	1.141	1.139	1.143
Law school tuition	–0.00012	0.0000007	29872.5481	<.0001	1	1	1
Black/African American	–0.6815	0.0251	737.4078	<.0001	0.506	0.482	0.531
White/Caucasian	0.0331	0.0166	4.0058	0.0453	1.034	1.001	1.068
Hispanic/Latino	0.1218	0.0248	24.1033	<.0001	1.13	1.076	1.186
Asian/PI	0.0227	0.0246	0.8474	0.3573	1.023	0.975	1.074
American Indian/Alaska Native	–0.0964	0.0686	1.9732	0.1601	0.908	0.794	1.039
Female	0.0615	0.0101	37.1414	<.0001	1.063	1.043	1.085
LGBT	–0.1651	0.0321	26.3763	<.0001	0.848	0.796	0.903

Distance Traveled: Linear Regression and Multilevel Modeling

The overall average distance students go for law school is 384.74 miles; the median distance is 101.5, indicating distance traveled for law school is a positively skewed variable.

Over the time period observed, distance traveled for law school rose from a median distance of 98.4 in fall 2008 to 109.6 in fall 2010, then declined to a median value of 92.4 in fall 2013. Figure 1 illustrates this trend as it compares to the total number of ABA applicants applying to law school. As evident from the figure, the trends closely mimic each other.

Figure 1



Naturally, students differed in distance traveled for law school depending on their home state. A complete list of median miles traveled by state can be found in Table 7. Students from Alaska traveled the furthest median distance, with a median of 2,333 miles traveled for law school, followed by students from Utah (584 miles), Colorado (579), Idaho (337), and Montana (298). Students from Minnesota, Massachusetts, Maryland, New York, and Oklahoma traveled the least (24, 29, 36, 39, and 40 miles respectively).

Table 7

Median Distance in Miles Traveled for Law School by State of Permanent Residence

Permanent State	*n*	*Mdn*	Permanent State	*n*	*Mdn*
AK	385	2,333	DE	701	77
UT	3,091	584	OH	8,864	72
CO	3,694	579	CT	3,768	71
ID	891	337	IL	11,382	71
MT	771	298	MI	7,473	70
AZ	4,113	296	LA	3,880	62
NV	1,674	267	NJ	10,423	49
TN	3,584	225	RI	884	49
WA	4,939	222	NE	1,362	47
ND	501	215	OK	2,150	40
WY	366	209	NY	24,676	39
DC	2,824	202	MD	6,560	36
SD	554	201	MA	7,450	29
TX	18,083	195	MN	4,289	24
NM	1,135	191			
VT	447	180			
FL	19,835	160			
OR	2,253	145			
WI	3,708	141			
MS	1,642	138			
GA	7,609	134			
HI	961	131			
VA	8,091	128			
WV	1,134	127			
AL	2,522	125			
KS	1,980	125			
MO	4,106	119			
IA	1,955	118			
SC	3,028	115			
NC	6,903	110			
ME	818	110			
IN	4,075	101			
CA	33,109	87			
AR	1,622	87			
PA	10,460	85			
KY	2,976	84			
NH	863	80			

Distance traveled for law school was positively correlated with law school tuition[4] (0.25), the number of applications a student submitted (0.23), the selectivity[3] of the law school (0.20), the number of accepted applications (0.17), and average LSAT score (0.15).

Averages along important demographic and undergraduate characteristics were calculated, in addition to Cohen's d effect size (ES) using a SAS macro (Kadel & Kip, 2012). Cohen's d ES measures the standard magnitude of association between two variables (e.g., students indicating an LGBT status versus non-LGBT students), and is generally calculated as the mean difference between these two variables over a pooled measure of their standard deviation. We used this ES because of its base rate–insensitive nature, base rate being defined as the number of subjects in one variable group versus the other. As this ratio departs from 50/50, the generally used r correlation ES will be increasingly small, and will not reflect an effect observed in a very small sector of the population (McGrath & Meyer, 2006). As LGBT students comprise only 3% of law school matriculants, and many other important demographic groups we considered were a small segment of law school matriculants, Cohen's d ES was calculated to represent differences in distances traveled among various subgroups. While the literature varies on what is considered a large or small ES, .60 is often considering to be a large ES, .30 considered moderate, and .10 considered small (Synder & Lawson, 1993, p. 345).

Table 8 displays average distances traveled by groups of students based on race/ethnicity. Asian/PI matriculants were more likely to travel far distances than others, with a moderate ES. American Indian/Alaska Natives traveled a further distance than others, with a small ES. Hispanic matriculants are more likely than non-Hispanics to travel far distances, though with a very small ES. Black/African American matriculants travel a slightly higher average distance to law school than others, though again the ES is very small. White/Caucasian students are less likely than non-White/Caucasian matriculants to travel far distances for law school with a small to moderate ES. That Hispanic/Latino students are likely to travel far distances, but remain within their state, is an interesting finding. Perhaps this is due to large Hispanic/Latino populations in big states such as Texas, California, and Arizona, so that while many Hispanic/Latino students remain in state, they are still traveling large distances. Further research is needed to determine the truth of this hypothesis.

Table 8
Average Distance in Miles Traveled to Law School by Race/Ethnicity

Student Race/Ethnicity	*N*	*M*	ES
Asian/Pacific Islander	18,500	532	0.26
American Indian/Alaska Native	1,432	449	0.10
Hispanic/Latino	18,124	433	0.08
Black/African American	20,109	393	0.02
White/Caucasian	173,667	354	-0.15
All	260,564	385	

Female students traveled shorter distances than their male counterparts, though with only a small ES, as shown in Table 9.

Table 9
Average Distance in Miles Traveled to Law School by Gender

Gender	*N*	*M*	ES
Female	121,934	378	−.02
Male	137,457	389	

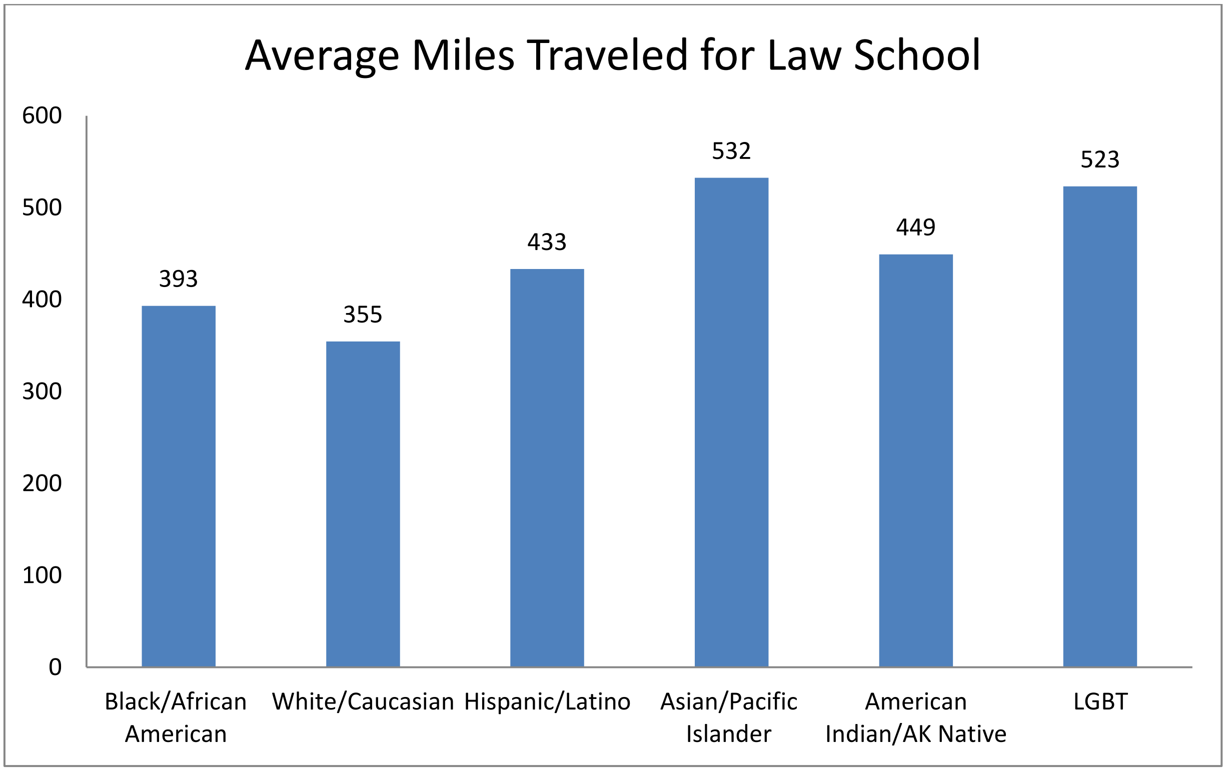
LGBT matriculants were more likely to travel far distances for law school, with a moderately large ES, as seen in Table 10.

Table 10
Average Distance in Miles Traveled to Law School by LGBT Status

LGBT Status	*n*	*M*	ES
LGBT	6,618	523	.23
Non-LGBT	253,130	381	

Figure 2 displays the average miles traveled for law school by race/ethnicity and LGBT status. When interaction effects were tested between gender and race/ethnicity and between gender and LGBT status, female students were less likely to travel far distances in all of the categories, though ES was generally small.

Figure 2



Looking at the characteristics of undergraduate schools students attended in Table 11, students from public undergraduate college were less likely to travel far for college, though with a small ES. Attending a top[2] college indicates matriculants are more likely to travel farther for law school, with a moderate ES.

Table 11
Average Distance Traveled to Law School in Miles by Undergraduate Characteristics

Undergraduate Characteristic	*n*	*M*	ES
Public	149,198	365	−0.10
Non-Public	96,375	423	
Top College	9,475	565	0.30
Non-Top College	250,273	378	

The parameters for the linear regression model that best represented our data (as discussed in the Methods section) can be found in Table 12. This model explains 24% of the variation in distance traveled to law school, as indicated by the 0.2352 R-square. The model indicates that for an increase in 1% of the percentage of law schools applied to in region, a student is likely to stay about 8 miles closer to home, all other variables held constant. Number of acceptances is negatively related to distance in our model, though a simple correlation indicated a positive relationship to distance, albeit a fairly small correlation of 0.17. Also in the model, being Black/African American indicates a likelihood of staying about 13 miles closer to home, which is likewise different from the previously discussed indicators that generally indicated Black/African American students were slightly more likely to travel further, though with a very small ES of 0.02. Because of the small correlation and ES in these variables, and because in the model many variables are held constant, the shift in sign in both number of acceptances and Black/African American is not particularly surprising. Average LSAT remains positively associated with distance, as does law school tuition. Because law school tuition is measured in dollars, an increase in every $1,000 of tuition can be interpreted to indicate that the student will go to law school an additional 7.1 miles further, holding the other variables constant. Also positively related to distance is the number of law schools in the student's home state, as well as being Hispanic/Latino, Asian/PI, American Indian/Alaska Native, and LGBT. Fall semester, as well as being Black/African American, White/Caucasian, and Female, are negatively associated with law school distance. All parameter estimates are statistically significant.

Table 12
Parameter Estimates for Linear Regression Modeling Distance Traveled for Law School

Variable	Parameter Estimate	*SE*	*t* Value	$p > \lvert t \rvert$	CI	
Intercept	24,873	1462.98	17	<.0001	22,005	27,740
Percentage of law schools applied to within region	–8.05231	0.03768	–213.7	<.0001	–8.1262	–7.9785
# of acceptances	–4.91368	0.4103	–11.98	<.0001	–5.7179	–4.1095
Average LSAT	0.44939	0.16923	2.66	0.0079	0.11769	0.78108
LS tuition	0.00709	0.00013	55.27	<.0001	0.00684	0.00734
Fall	–12.141	0.72612	–16.72	<.0001	–13.564	–10.718
# of law schools in home state	10.49765	0.19919	52.7	<.0001	10.1072	10.8881
Black/African American	–12.591	5.57782	–2.26	0.024	–23.523	–1.6586
White/Caucasian	–37.0262	3.75832	–9.85	<.0001	–44.392	–29.66
Hispanic/Latino	28.0935	5.59477	5.02	<.0001	17.1279	39.0591
Asian/PI	47.07938	5.51827	8.53	<.0001	36.2637	57.895
American Indian/AK Native	77.6163	15.6402	4.96	<.0001	46.9619	108.271
Female	–8.71981	2.29642	–3.8	0.0001	–13.221	–4.2189
LGBT	58.86951	7.18041	8.2	<.0001	44.7961	72.9429

Note. df=1 for each variable.

The final model on which we reported results was a multilevel model that nested students by their state of permanent residence. The parameters can be found in Table 13. The number of law schools in the student’s home state, as well as the many races/ethnicities including White/Caucasian, Hispanic/Latino, Asian/PI, and American Indian/Alaska Native are no longer statistically significant once we consider students as nested within their home state. Black/African American is here positively associated with distance. Number of acceptances is again negatively associated with distance as in the linear model, and this time average LSAT score is slightly negatively associated with distance traveled.

Table 13
Parameter Estimates for Multilevel Model (Students Nested Within Home State) Predicting Distance Traveled for Law School

Effect	Estimate	*SE*	*df*	*t* Value	*p* > |t|
Intercept	37,642	1410.52	49	26.69	<.0001
Percent of law schools applied within region	–7.6995	0.03683	240,000	–209.05	<.0001
# of acceptances	–4.0101	0.3919	240,000	–10.23	<.0001
Average LSAT	–0.5284	0.1624	240,000	–3.25	0.0011
LS tuition	0.0103	0.000133	240,000	77.43	<.0001
Fall	–18.429	0.6998	240,000	–26.34	<.0001
# of law schools in home state	–5.7186	8.8102	240,000	–0.65	0.5163
Black/African American	38.4741	5.3665	240,000	7.17	<.0001
White/Caucasian	–5.782	3.5941	240,000	–1.61	0.1077
Hispanic/Latino	5.9251	5.3918	240,000	1.1	0.2718
Asian/PI	7.0248	5.278	240,000	1.33	0.1832
American Indian/Alaska Native	28.2679	15.0191	240,000	1.88	0.0598
Female	–10.0088	2.1915	240,000	–4.57	<.0001
LGBT	45.0693	6.8451	240,000	6.58	<.0001

Discussion

With a wealth of data at its disposal, LSAC is in a unique position to research patterns of application and matriculation behaviors in higher education. Below, we will discuss the main areas of investigation using the main analytical subgroups of within-state analyses and distance traveled analyses.

Within State Analyses and Limitations. Given the increasingly difficult market pressures targeting law schools and higher education in general, we theorized that some potential law school students would be enticed to matriculate at their in-state institutions because of perceptions of cost savings, or because of the desire to stay near home. We further theorized that this effect may be greater for some subpopulations. Ultimately, we found that many factors played a role in the decision to enroll at a law school within state versus out of state. Confirming our theories, applicants who attended 2-year (community) colleges and public universities were more likely to select an institution in state, whereas graduates from top undergraduate institutions were more likely to leave their state for law school.

We were not particularly surprised by our identity group analyses, which showed that Black/African American matriculants were least likely among all ethnic groups to stay in state. Similarly, the fact that Hispanic/Latino matriculants most often stayed in state confirmed our hypotheses. Likewise, we had hypothesized that LGBT students may be more willing to leave their respective states, perhaps for specialized law programs or to live in more socially progressive areas, but we were astonished by the large magnitude of the effect. Among all our subgroups, LGBT applicants were the most likely to leave their home state for law school. Keeping in mind that there was notable variation within the LGBT group in terms of gender, ethnicity, and age, the fact that these matriculants most often left their respective states is a noteworthy effect. Now that we are aware of the effect, we intend to pursue this topic further. One limitation of the within-state analyses is that there are states that have larger cities situated near their borders. Thus, applicants may matriculate at a law school that is technically out of state, but one that is nevertheless located nearby. An example of this issue would be New Jersey residents traveling with relative ease into Philadelphia or New York City metro area law schools.

Distance Traveled Analyses and Limitations. Distance traveled proved a rather complicated variable to address effectively, but one we thought important to include in our research, partly to address the limitations of the parsimonious, but restrictive, state-level analyses. Unsurprisingly, being so far from the mainland of the U.S. and having no law school of its own, Alaskan residents traveled the farthest. More surprising were states such as Minnesota, Massachusetts, and Oklahoma, which had the smallest median distances traveled. The explanation for this outcome is unclear, but we hope to investigate further. Among ethnic groups, Black/African American, Hispanic/Latino, and American Indian/Alaskan Native matriculants were more likely to travel somewhat longer distances for law school, but the effect sizes were small. White/Caucasian matriculants tended to travel shorter distances compared to their non-White/Caucasian peers. The significant effect of distances traveled for Black/African American matriculants supports results found in the literature. With the largest total effect size, however, Asian/Pacific Islander matriculants traveled farther than non-Asian/Pacific Islanders, which is opposite the outcome reported in the existing literature. Switching from the linear model to the multilevel model, many ethnic effects were no longer significant, except for Black/African American matriculants. We were hoping to confirm our linear analysis in the multilevel model, but clearly a complex effect is occurring, which we will pursue in future research.

Regardless of ethnic group affiliation, female matriculants traveled very slightly shorter distances than their male counterparts, but with only a small effect size. It seems this effect is quite small and deserves additional research to clarify whether the effect is too small to be of practical significance. Of notable significance was LGBT matriculants, with the second largest effect size for traveling farther than non-LGBT matriculants, with an average distance of over 500 miles. Obviously, this surprising outcome deserves further analysis. For undergraduate university factors, matriculants attending a public undergraduate institution were less likely to travel far for law school, whereas attending a top undergraduate institution is associated with traveling greater distances for law school. Presumably, graduates from top institutions are more competitive and seek to matriculate at highly selective law schools, thus making them willing to travel farther to reach that goal.

Given our massive sample sizes and our large amount of demographic data, we thought that this distance analysis would be useful to both researchers and admission officers. These results, however, were not without their limitations. One problem we encountered was the data distributions. Some skewness within subpopulations often occurs, and our data were no exception. Skewness can bias analyses so that effects are artificially exaggerated or minimized. Data transformations, such as a log transformation, may yield more accurate results. In addition, our results for both sets of analyses may not be fully generalizable outside of the law school applicant population. Our goal is to present enough information for researchers to use this method to examine their own databases or perhaps other large-scale databases such as Higher Education Research Institute (HERI) or federal education data.

Conclusions and Future Directions

Our research confirms much of the prior research but also complicates it, making a case for targeting admission marketing based on subgroup information. While our current results cannot yet suggest specific admission marketing recommendations, we hope to be able to provide more specific information by expanding our research in the future. We plan to accomplish these refinements by addressing the methods, analyses, and databases. For the methods and analyses, we hope to refine our analytical model and determine how the unexplained differences between the in-state model and the distance model work. From there, we can further refine our model and perhaps create structural equation models or hierarchical linear models to better clarify our outcomes. It may be useful, for example, to examine whether or not matriculants choose regions but not necessarily states. As we have created our current models, it is unclear whether there are moderator or mediator effects that we omitted but that could improve our models and explanations. Lastly, given our large datasets and the lack of consistency of some results, we may want to use explore data reduction techniques such as factor analysis or cluster analysis.

Further, we hope to combine our data with the data available from the HERI Cooperative Institutional Research Program (CIRP) so that we can delve further into the longitudinal aspects of student choice in selecting a law school. Previous research on distance traveled for higher education found a notable impact for variables such as parental education and income. By merging our data with HERI-CIRP data, we would be able to further elucidate student institutional choice behaviors. In addition, we would like to investigate metro areas as separate location variables that could be attractive to potential matriculants. We theorize that some students would choose metro areas because of employment, internship, or personal opportunities that may not be available elsewhere. Finally, we hope to expand these results to include measurable results, such as examining the impact of distance traveled on first-year performance in law school.

In this paper, we discussed in-state behaviors as well as overall distance traveled to attend law school. Our goal was to assist researchers and admission officers in targeting students for marketing purposes, and we revealed some of the differences within the subpopulations of law school matriculants. Our hope in this research project was to create a summary of matriculants' willingness to travel to a law school by using varied analytical techniques. Future research will both broaden and deepen our current strategy with the goal of ultimately achieving a fuller understanding of essential admission issues and applicant matriculation behaviors.

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Predicting Four-Year Student Success from Two-Year Student Data

Paper Submitted to NEAIR November 2014

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INTRODUCTION

The landscape of higher education shows an increasingly diverse student body and an equally diverse set of institutions (Archer, Hutchings, & Ross, 2005; Cross, 1981). Many issues faced by higher education institutions relate to student success. Specifically, issues of access, affordability, and value (return on investment) are frequently examined by academics, institutions, governing boards, and the legislature (e.g., Bamber & Tett, 2000; Miller & Lu, 2003; Thomas, 2002). Most of the research in these areas has centered on first-time, full-time, degree-seeking undergraduates (e.g., Bers & Smith, 1991). While this sub-population represented the majority of students in past decades, the student market has expanded and shows an increasing population of non-traditional students, that is, transfer, part-time, and adult (Bean & Metzner, 1985). Non-traditional students tend to have lower access to post-secondary education and lower success rates when enrolled as compared to traditional students (Grimes, 1997; Spitzer, 2000).

Of the population of students who enter community college, 81% intend to complete a bachelor's degree; however, only about 12% of these students earn a bachelor's within six years of transferring to a four-year institution (Community College Research Center, 2014). In part, this may be because non-traditional students are more likely to attend college part time and to be balancing academic commitments with work or family obligations. Because of the discrepancy in student ambition and achievement, community college transfer students at a four-year university are the population of interest in this study.

The impetus for this project was to define and evaluate the academic pathways of community college transfer students earning a four-year degree. The University of Maryland University College (UMUC), funded by the Kresge Foundation, partnered with Montgomery College (MC) and Prince George's Community College (PGCC) to identify factors associated with community college transfer student success. While current literature, has focused primarily on graduation, we were interested in examining a variety of academic milestones student must pass in earning a credential. Defining such milestones (e.g., re-enrollment, retention) proved difficult, as UMUC is an online university serving primarily non-traditional learners, who may be more likely to have discontinuous enrollment pathways in higher education. Tracking non-traditional students' persistence in an online content, presents challenges resulting from issues associated with data management, reliable and valid variable definitions, and model complexity (Park and Choi, 2009).

The purpose of this study was four-fold:

1. To develop a collaborative relationship between two community colleges and one four-year institution,
2. To develop an integrated database that includes key information on student demographics, course taking behavior, and performance
3. To analyze data using data mining and statistical techniques to predict student success
4. To develop, implement, and evaluate interventions designed to improve student success.

This project was guided by a cross-institutional, collaborative workgroup that included external evaluators who validated the integrity and relevance of the research.

STUDENT POPULATION

UMUC identified all students enrolled between Spring 2005 and Spring 2012. Of these students, MC and PGCC identified students who had an academic record at their institution at any point in time. Some students identified had attended community college more than five years prior to enrollment at UMUC. Across both MC and PGCC, 32,000 students were identified for analysis. The population was reduced to include only students whose first enrollment at UMUC was between 2005 and 2012. The analyses presented in this paper focus on students who transferred from one of these two institutions and whose first enrollment at UMUC was between Spring 2005 and Spring 2012. The final dataset included 8,058 students, with 59% (n=4724) from MC and 40% (n=3220) from PGCC.

DATA

UMUC and partner community colleges developed a Memorandum of Understanding (MOU) that continues to guide the collection and use of data. An Oracle database was developed to hold the data. All data are securely stored, with restricted access.

Each institution provided demographic and performance data about each of the students in the population. Over 300 natural and derived variables were collected or generated and stored in the database. UMUC's Institutional Research office created a data dictionary that was used to guide data integration and research on student success.

VARIABLE DEFINITIONS

Based on a review of the literature, institutions worked collaboratively to define student success, align data definitions, and determine which factors were most important to consider in predictive modeling.

Success has been defined in a variety of ways in the research literature, including as degree completion and the various benchmarks the lead to completion (Park & Choi, 2009). For this project, four indicators of student success were identified: successful first term GPA, re-enrollment, retention, and graduation. Each of these success metrics is defined:

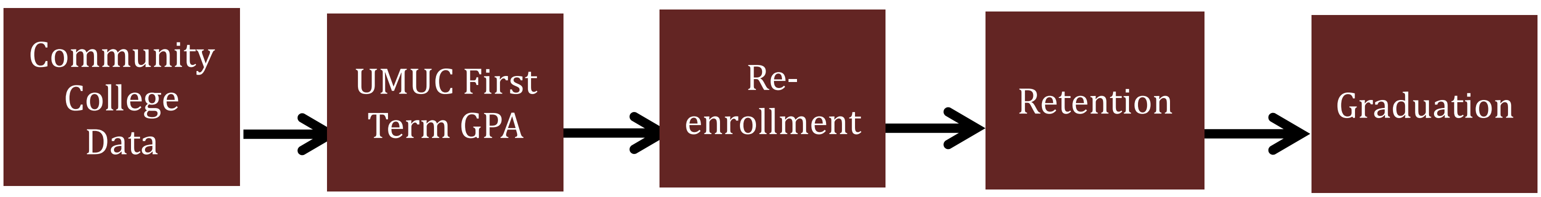
- **Successful First Term GPA** – Average of all course grades received in the first semester of enrollment at UMUC that is 2.0 or above, on a 4-point scale
- **Re-enrollment** – Enrollment in the immediate next semester after initial enrollment at UMUC
- **Retention** – Re-enrollment at UMUC within 12 months after initial enrollment
- **Graduation/Degree Completion** – Earning a first bachelor's degree from UMUC within eight years of transfer from the community college

These definitions were developed by reviewing a number of sources including: 1) the literature on retention and online learning; 2) institutional publications, such as reports to the Middle States Commission of Higher Education, studies on retention or course success, and the course catalogs, and 3) common definitions used within the institutional research community.

RESEARCH

Based on a review of the literature, a theoretical model of students' academic trajectories from the community college to graduation was developed (Figure 1). This model included key milestones in students' progress including earning a successful first-term GPA, re-enrolling in the immediate next semester after transfer, and being retained within a 12-month period.

Figure 1. Model of Academic Trajectory



First, students' demographic characteristics and community college academic data were used to predict first term GPA at UMUC. Next, demographic characteristics and community college data were used alongside first-time variables to predict re-enrollment and graduation.

In this case, first-term GPA was both a target outcome and a predictor of later persistence. The dual role of earning a success first-term GPA reflects both the need for students to perform well in their first semester of transfer and the role the first semester plays in setting students up for later achievement and persistence.   There are three areas of research this paper will address:

1. Predicting first term GPA
2. Predicting re-enrollment
3. Predicting graduation

Logistic regression was used to predict each of these outcome varaibles.

RESULTS OF PREDICTIVE MODELING

Predicting First Term GPA

The model predicting students earning a successful first term GPA was significant, $X^2(21) = 756.43$, $p<0.001$, correctly classifying 76.8% of students as earning a successful first-term GPA or not. Cox and Snell's R^2 suggested that the model explained 9.1% of variance in earning a first term GPA, while Nagelkerke's R^2 suggested at 13.7% of variance had been explained. See Table 1.

Table 1
Predicting first term GPA using demographic characteristics, community college course taking behaviors, and summative measures of CC Background

		β	SE(β)	Significance	β*
Demographic Characteristics					
Gender*		**0.12**	**0.06**	**0.043**	**1.13**
Age**		**0.01**	**0.00**	**0.001**	**1.01**
Race/ Ethnicity: Compared to White	**Black*****	**-0.36**	**0.08**	**0.000**	**0.70**
	Hispanic/Latino	-0.10	0.11	0.367	0.91
	Asian	-0.06	0.11	0.57	0.94
	American Indian	-0.28	0.27	0.30	0.76
	Race Not Specified*	**-0.23**	**0.10**	**0.021**	**0.79**
Marital Status**		**0.25**	**0.08**	**0.001**	**1.29**
PELL Grant Recipient***		**-0.30**	**0.07**	**0.000**	**0.74**
Community College Course Taking					
Successful Course Completion Overall***		**1.63**	**0.21**	**0.000**	**5.08**
Successful Math Completion**		**0.20**	**0.06**	**0.004**	**1.22**
Successful English Completion**		**0.18**	**0.06**	**001**	**1.20**
Developmental Math Completion**		**0.27**	**0.08**	**0.001**	**1.31**
Developmental Writing Completion		-0.08	0.10	0.38	0.92
Developmental Reading Completion		-0.07	0.11	0.48	0.93
Developmental Math Exempt		-0.03	0.08	0.747	0.97
Developmental English Exempt		-0.11	0.05	0.07	0.89
Repeated Courses		-0.27	0.07	0.000	0.76
Summative Measure of CC Background					
GPA***		**0.22**	**0.05**	**0.000**	**1.25**
Credits Earned		**-0.001**	**0.002**	**0.62**	**1.00**
Associates Received***		**0.39**	**0.08**	**0.000**	**1.47**

Note: *sig. at 0.05 level, ** sig. at 0.01 level, *** sig, at 0.001 level

Among demographic characteristics, gender, age, and marital status were all significant predictors in the model. Specifically, students who were female, older, and married were significantly more likely to earn a successful first term GPA at UMUC. At the same time, students' reporting their race/ethnicity as African American or not designating a race/ethnicity were less likely to earn a successful first term GPA. Further, receiving a PELL grant at the community college, as an indicator of financial need, decreased the likelihood of students earning a successful first term GPA.

In examining indicators associated with students' community college course taking behaviors, students' overall rate of successful course completion and rate of successful math completion and successful English completion were all significant predictors in the model. Further, students completing of developmental math was a significant predictor in the model.

Among the summative measures of community college performance, cumulative GPA and earning an Associates degree were both significant predictors. Examining the standardized betas determined that, holding all else constant in the model, students' overall rates of successful course completion carry the most impact in increasing students' probability of earning a successful GPA.

Predicting Re-Enrollment

The overall model for re-enrollment was significant, $X^2(19) = 1063.24$, $p<.001$. The model was able to correctly classify 71.6% of students as re-enrolling or not. Pseudo R^2 measures of effect size ranged from an estimated 12.5% of variance in re-enrollment explained (Cox & Snell's R^2) to 17.4% of variance (Nagelkerke's R^2) explained. See Table 2.

Table 2

Predicting re-enrollment using demographic characteristics, community college course taking behaviors, summative measures of CC backgrounds, and UMUC first-term indicators

	β	SE(β)	Significance	β*
Demographic Characteristics				
Gender* **	**0.20**	**0.05**	**0.000**	**1.22**
Age	0.00	0.00	0.638	1.00
Race/ Ethnicity: Compared				
Black*	**0.17**	**0.07**	**0.013**	**1.19**
Hispanic/Latino	-0.02	0.10	0.83	0.98
Asian	0.07	0.10	0.492	1.07
American Indian	0.19	0.27	0.469	1.21
Race Not Specified*	**0.05**	**0.09**	**0.60**	**1.05**
Marital Status* *	**0.24**	**0.07**	**0.001**	**1.28**
PELL Grant Recipient	0.13	0.07	0.065	1.14
Community College Course Taking				
Repeated a Course* *	**0.17**	**0.06**	**0.005**	**1.19**
Enrolled in a Developmental Course* **	**0.21**	**0.06**	**0.001**	**1.23**
Exempt from Developmental Math* *	**0.22**	**0.08**	**0.004**	**1.25**
Summative Measures of Community College Backgrounds				
Community College GPA* *	**-0.11**	**0.04**	**0.005**	**0.89**
Cumulative Credits Earned at CC	-0.00	0.00	0.208	1.00
Earned an Associate's Degree	-0.13	0.07	0.059	0.88
First Term at UMUC				
First Term GPA* **	**0.26**	**0.02**	**0.000**	**1.30**
First Term Credits Earned* **	**0.14**	**0.01**	**0.000**	**1.14**
Enrolled Full Time	-0.16	0.08	0.054	0.86
Cumulative Credits Transferred* **	**0.01**	**0.00**	**0.000**	**1.01**

Note: *sig. at 0.05 level, ** sig. at 0.01 level, *** sig, at 0.001 level

Examining demographic characteristics determined that gender and marital status were both significant predictors in the model. Specifically, being female and married increased students' probability of re-enrolling in a subsequent term at UMUC. Further, unlike with first term GPA, race/ethnicity designated as African American or unspecified were significantly positive predictors of re-enrollment.

In examining students' community college course taking behaviors, different predictors than those found to be significant in predicting performance were identified. Specifically, students' likelihood of re-enrollment increased if they either enrolled in a developmental course or were exempt from developmental math. Repeating a course at the community college was found to be a significant, positive predictor of re-enrollment; in other words, re-taking a course in community college increased the likelihood that students' would re-enroll.

Among summative measures of students' community college performance, only community college GPA was a significant predictor in the model. Further, despite being a positive predictor of first-term GPA, community college GPA was a negative predictor of persistence or re-enrollment. More work is needed to understand why this may be the case.

At the transfer institution, first term GPA and total number of credits earned were significant predictors of re-enrollment. Further, the cumulative number of credits transferred was a significant positive predictor in the model.

Predicting Graduation

The logistic regression model predicting eight-year graduation was significant, $X^2(17) = 1271.59$, with 69.6% of cases correctly classified as graduating or not. Effect size measures suggest that between 20.0%, according to Cox and Snell's R^2, and 26.7%, according to Nagelkerke's R^2, of variance in graduation was explained by the model. See Table 3.

Table 3

Predicting graduation using demographic characteristics, community college course taking behaviors, summative measures of CC backgrounds, and UMUC first-term indicators

	β	**SE(β)**	**Significance**	**β***
Demographic Characteristics				
Gender	.029	.106	.785	1.029
First_Term_Age* **	**-.023**	**.007**	**.000**	**.977**
Minority Status	-.169	.104	.104	.845
Receiving PELL at CC	-.262	.167	.116	.770
Community College Course Taking				
Math Enrollment at CC*	**.329**	**.135**	**.015**	**1.390**
Percent Ws at CC	-.670	.381	.079	.512
Summative Community College Measures				
Receiving AA at CC	.127	.129	.325	1.135
CC CUM GPA*	**.168**	**.081**	**.038**	**1.184**
CC Credits Earned	.005	.003	.059	1.005
UMUC First Term Indicators				
UMUC First Term GPA***	**.482**	**.044**	**.000**	**1.619**
UMUC First Term Creds Earned***	**.021**	**.002**	**.000**	**1.022**

Note: *sig. at 0.05 level, ** sig. at 0.01 level, *** sig, at 0.001 level

Of demographic traits examined, only first term age when transferring to UMUC was found to be significant; being younger increased students' likelihood of graduating.

Examining course work at the community college, enrolling in a course in the Math subject area was a significant predictor of graduation. In terms of summative, community college course taking indicators, community college cumulative GPA was a significant positive predictor. Students' GPA in the first semester and the number of credits earned in their first term were significant positive predictors.

INTERVENTIONS

In addition to the research, this project included the development, implementation, and evaluation of interventions designed to improve transfer student success. These interventions were undertaken at both the community colleges and at the four-year institution. Based on a review of the literature, three areas of student success were targeted for intervention:

(a) academic achievement

(b) social and institutional integration

(c) goal setting and academic planning

Following are brief descriptions of interventions undertaken and intervention results.

1. Accounting 220 and Accounting 221

In collaboration with the Predictive Analytics Framework (PAR, www.parframework.org), a Gates Foundation funded project, the Predicting Student Success Project team identified Accounting 220 and 221 as a course sequence with low course completion rates compared with other UMUC courses. The UMUC faculty teaching Accounting 220 and Accounting 221 developed and implemented an online tutoring intervention for UMUC accounting students. The Predicting Student Success Project team evaluated the effectiveness of the online tutoring intervention. Students participating in online tutoring had a significantly higher term GPA and a significantly higher rate of successful course completion, when compared to students not participating in online tutoring.

	Test Participating in Online Tutoring	**Control** Not Participating in Online Tutoring
Term GPA	2.52	2.10
Successful Course Completion	72%	58%
Re-Enrollment	78%	72%

2. New Student Orientation Checklist

A New Student Orientation Checklist was developed as an aid for community college students transferring to UMUC to assist them in navigating online resources available from UMUC. For example, students were asked to find their advisor's contact information and to identify the time and location that math and statistics tutoring was available. Although no significant differences were found, students responding to a survey found the checklist to be a useful tool. One student reported: "It helped me compile information and learn how to use UMUC's website." UMUC has developed and launched a broader checklist to help all students prepare for their academic careers at UMUC and for graduation.

	Test Received the Checklist	Completed the Checklist	**Control** Did Not Receive the Checklist
Term GPA	2.87	3.00	2.91
Successful Course Completion	73%	77%	77%
Re-Enrollment	67%	72%	67%

3. College Success Mentoring Program

The College Success Mentoring Program was an eight-week structured mentoring program in which students who had transferred from MC or PGCC to UMUC were paired with a peer mentor – a successful student at UMUC who had also transferred from the same community college. Each week, mentors contacted mentees to provide academic and social support and to help with mentees' adjustment to UMUC. Although no statistically significant improvements in semester performance were found for mentees, unexpectedly, students serving as mentors had a significantly higher cumulative GPA and a significantly higher rate of successful course completion when compared to a control group of students who were invited to be mentors and elected not to participate.

	Mentees	
	Test	**Control**
GPA	2.70	2.66
Successful Course Completion	78%	69%
Re-Enrollment	74%	75%
	Mentors	
	Test Served as mentors	**Control** Invited but did not serve as mentors
GPA	3.56	3.34
Successful Course Completion	95%	89%

4. JumpStart

JumpStart was developed as a four-week onboarding course for students new to UMUC, designed to support students' academic planning. Jumpstart was offered to students in Spring 2014 and found to improve successful course completion. In Summer 2014, UMUC ran a pilot experiment to judge the effectiveness of jointly offering the Jumpstart course and mentoring to community college transfer students. Students participating in Jumpstart and in the mentoring program were compared to a control group and to students participating in only one of the programs (i.e., only in Jumpstart or only mentoring). No significant differences in performance were found; however, development of Jumpstart continues at UMUC based on previous evidence of its success.

	Test Enrolled in Jumpstart	Completed Jumpstart	**Control** Did Not Enroll in Jumpstart
Term GPA	2.42	3.06	2.69
Successful Course Completion	61%	89%	74%
Re-Enrollment	76%	91%	75%

5. Women's Mentoring, Boys to Men, TRiO

The Women's Mentoring, Boys to Men, and TRiO mentoring programs, developed by Montgomery College, provide minority students with comprehensive academic and social support throughout their transfer pathways from high school to MC and ultimately to a four-year institution. MC and UMUC will identify students participating in these programs transferring to UMUC and will track them to evaluate their performance.

6. Diverse Male Student Initiative

Diverse Male Student Initiative (DMSI) is a two-year program at Prince George's Community College that provides minority male students with role models and academic and career mentoring. DMSI held a two day summer institute that featured keynote speakers and awarded book and tuition vouchers for early registration to participants with the aim of improving academic planning and persistence. PGCC and UMUC will track and evaluate the success and persistence of students who participated in this program and who transfer to UMUC.

CONCLUSIONS AND IMPLICATIONS

Based on work completed as part of this collaborative project, a number of conclusions may be drawn.

1. **Demographic Factors**: Gender and marital status were associated with both performance (i.e., earning a successful first-term GPA) and persistence (e.g., re-enrollment). These characteristics may indicate students' maturity and commitments to pursuing academic goals. Interestingly, minority status behaved in unexpected ways in analyses. Specifically, while African American status was negatively associated with earning a first-term GPA, it was positively associated with persistence metrics. This suggests that while not always successful, in terms of performance, in the first semester, African American students may nonetheless be committed to their educational goals. Further, such findings point to the importance of considering both performance and persistence as independent factors contributing to students' success.

2. **Math at the Community College:** Across models examining both persistence and performance, variables associated with taking math at the community college were

found to be significant predictors. In the literature, math has been discussed as a course key to transfer students' academic preparation for a four-year institution. Within our sample, taking math at the community college, in addition to reflecting academic abilities, may also reflect students' commitment to meeting the requirements necessary for transfer and graduation. Further, both factors associated with completing developmental math and enrolling in math courses overall were significant. This suggests that it is not *high* math achievement that necessarily contributes to success but rather electing to take courses presenting such added difficulty.

3. **First Term Performance:** Students' performance in the first semester at UMUC remains crucial in predicting their re-enrollment, retention, and graduation. In fact, across models, it was the strongest individual predictor of performance. First term GPA may be an indicator of factors contributing to students' success, beyond academic abilities. Specifically, students who are better acclimating to an online university and the demands associated with a four year institution may have a higher first term GPA. Earning a successful GPA in-and-of itself may in turn encourage students to persist in their educational goals.

4. **Instructor Driven Interventions:** Looking across interventions, interventions that were efficacious in promoting students' success were those that were instructor-driven. Specifically, Accounting 220 and 221 and Jumpstart were both effective in promoting students' success, in part because they were led by engaged instructors

who encouraged and worked closely with students. Further, these interventions were academic in nature and closely tied to course content. It may be the case that for online, non-traditional learners social and institutional integration (targeted through the new student checklist and the mentor program) is a secondary concern. These students may be more driven by academic pursuits and motivated to complete their course work as quickly as possible as such they may derive more benefits from course-specific, instructor-driven interventions.

5. Collaboration is Key: Across both research initiatives and interventions undertaken, collaboration between UMUC and the partner community college proved to be key. Particularly in addressing the needs of non-traditional students, enrolled in an online institution, a learning context about which there remains limited research, combining expertise was crucial. Community colleges have deep knowledge of their students' backgrounds- their insights guided research and intervention development. Pragmatically, data sharing enabled UMUC to gain access to students' transfer records from the community colleges that were more accurate than the information available in UMUC's Student Information System. This type of data sharing not only enabled research using predictive modeling to take into account students' community college backgrounds, but also ensured this research was based on valid data.

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PREDICTIVE MODELING: BENEFITS OF A BEGINNING STUDENT SURVEY

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Introduction

Research indicates that withdrawn students most often leave during their first year of college (Astin, 1993; Pascarella & Terenzini, 1991). As a result, many retention efforts focus on increasing first year engagement (Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008; Tinto, 1996). Institutions serving non-traditional students, particularly those with open enrollment and/or distance learning face specific challenges predicting student retention. These may include limited access to students' academic history, students' limited or inconsistent engagement, and different, if not fewer, forms of engagement to measure.

At Excelsior College, we have found that students who engage in at least one credit-bearing activity within their first year are more likely to be retained as well as to eventually graduate (Excelsior College, 2012; Excelsior College, 2014). A recurring question we face, however, is how best to allocate our human resources for outreach efforts. What indicators can we use instead of first year activity so that we can connect with students earlier?

This paper will assess at the ability of the Beginning Student Survey (BSS) to predict 15-month retention at Excelsior College (EC). Following is a comparison of logistic regression models with and without the survey data. We also compare these with our ability to predict retention with students’ variables at one year. While predictive ability at 12 months is expected to be strongest, the practical utility is limited because it leaves little to no time for meaningful intervention before 15-month retention. Further models separate nursing and non-nursing students to improve the predictive strength of the models for these distinct subpopulations.

Methodology

The aim here is to assess the utility of the Beginning Student Survey (BSS) items as predictors of student retention and completion. This report will describe the regression models compared and the logic behind final selection of models. The models shared in this report reflect 9 separate logistic regression models that each use Retention (a dichotomous variable) as the outcome variable.

Retention is measured at Excelsior at 15 months after a student's first enrollment with the college. The reasoning behind this is related to our enrollment fee schedule. When a student applies and pays an enrollment fee, he/she is then considered enrolled and is free to register for courses and exams. One year later, the student receives a bill for the next year's enrollment. It isn't until that payment is missed, at 15 months, that the student is switched from enrolled to withdrawn in our student information system. For this reason, we measure retention at 15 months so that it is a more accurate reflection than a 12-month rate would be. Whether or not a student is retained, or enrolled at 15 months post-enrollment, will serve as our dependent variable that we seek to predict.

All of the student data used here comes from one of three sources. The first is our Student Information System (SIS), which was internally developed as a transactional database for our student data. The second is a student warehouse, which populates on the 15th of every month and takes a snapshot of data from SIS. The last is survey data, which is pulled from Qualtrics, which we use to host and distribute our surveys at Excelsior College.

The Beginning Student Survey (BSS) is a 22-item survey that automatically goes out daily to all first time Excelsior students that enroll. The response rate is approximately 34%. Items cover topics such as expectations for academic progress, funding, experience and attitude, and expectations for engagement. For more detailed information about the BSS, please contact the author.

Three models predicting retention were compared for each the following groups: “Overall”, which includes all Excelsior students, “Nursing,” and “Non-Nursing.” For each of these three groups the following three models were compared: “Model 1: Intake”, “Model 2: Intake plus BSS items”, and “Model 3: Year One.” These models are meant only for comparison to see how closely we can approximate our ‘one year one predictive ability’ earlier with the help of the BSS information and better understand the predictive strength of the BSS.

The variables in Table 1 include all the variables selected for the models. Initial variables were included based on a study done by Hanover Research addressing Predictors of EC Retention reviewing data from 2007 and 2009 (Hanover Research, 2012). Models were then compared to achieve the best model fit and variables dropped as deemed appropriate. Although not discussed in detail here, data imputation procedures used involved used the mice package in R, which uses multiple imputation for chained equations. This is essentially uses a recursive variation of the EM (estimation-maximization) algorithm. Visual displays were also used to assess the impact of any missing data along with issues of multicollinearity. The variables shown below in Table 1 are those selected after all of these early processes.

Table 1: Variable List and Coding

Intake Variables (Used in Models 1, 2 and 3)
Gender: 2 level factor (Male*, Female)_
Ethnicity: 5 level factor (White*, Black, Hispanic, Asian, Unknown/Other)
Military Status: 3 level factor (Civilian*, Active, Veteran)
Level: 2 level factor (Associate*, Baccalaureate)
Division: 5 level factor (NU*, BU, HS, LA, TE)
Income Level: 2 level factor (Above 45k*, Below 45k)
English Language Native: 2 level factor (Yes*, No)
First Generation College: 2 level factor (No*, Yes)
First Service Evaluation: 4 level factor (0-4*, 5-24, 25-39, 40+)
Beginning Student Survey items (Used in Model 2)
EC Courses.Q1: 2 level factor (No*, Yes)
EC Exams.Q1: 2 level factor (No*, Yes)
Transfer.Q1: 2 level factor (No*, Yes)
Other Exams.Q1: 2 level factor (No*, Yes)
Portfolio.Q1: 2 level factor (No*, Yes)
Intended Pace.Q2: numerical (intercept represents 0)
Planned Time Off.Q3: 2 level factor (No*, Yes)
Expected Time To Completion.Q4: numerical (intercept represents 0)
Pay Confidence.Q7: 3 level factor (Yes*, Not Sure, No)
Last College Course.Q9: 3 level factor (Never*, In Past 5 Years, 5+ Years Ago)
Previous Online Course. Q10: 2 level factor (No*, Yes)
Previous Credit By Exam.Q11: 2 level factor (No*, Yes)
f1.College Prep: numerical (intercept represents 0)
f2.Motivation: numerical (intercept represents 0)
f3.Career Relevance: numerical (intercept represents 0)
Year One Variables (Used in Model 3)
EC GPA at 1 year: numerical (intercept reflects 0)
EC Hours Earned via Courses at 1 year: numerical (intercept reflects 0)
EC Hours Earned via Exams at 1 year: numerical (intercept reflects 0)
Transfer Hours Total at 1 year: numerical (intercept reflects 0)

The * denotes the reference group for dummy-coded variables

The three factors listed in Table 1 were created from a factor analysis that was conducted internally at Excelsior. Below are the BSS items that contribute to each factor.

- f1.College Prep: “I manage stress well”, “I can juggle multiple responsibilities”, “My family supports my decision to pursue a degree at this time”, “I am easily frustrated”, “I believe I am adequately prepared for college level mathematics”, “I believe I am adequately prepared for college level writing”, “I believe I am adequately prepared for college level reading”, and “It is important to me to finish what I start” (selected from BSS Question 11)
- f2.Motivation: “I want to be a college graduate”, “I am determined to earn a

college degree", and "I want to be a college graduate" (selected from BSS Questions 11 and 12)

- f3.Career Relevance: "I want to advance in my career", "I want to earn a higher salary", and "Without a college degree I cannot advance in my career" (selected from BSS Question 12)

By using these factors in lieu of the individual survey items, we avoid some concerns of multicollinearity between the similar items and we also achieve a more parsimonious model.

For each model, a logistic regression was used, which allows us to predict a binary outcome, retention, based on a group of predictors. Therefore the dependent variable, retention, is expressed as a logit and the intercept and coefficients should be interpreted differently from ordinary least squares (OLS) regression model. The logistic regression model is as follows, where y is the binary outcome (0,1), p is the probability that the binary outcome is 1, or in this case, the probability that a student is retained, and x_1, ... x_k are a set of predictors.

$$logit(p)=log(p/-1p)=\beta_0 +\beta_1 *x1+...+\beta_k *x_k \quad (1)$$

The logit can be converted to a probability, which is more easily interpreted. In terms of probabilities, the above equation can be expressed as:

$$p=exp(\beta_0 +\beta_1 *x_1+...+\beta_k *x_k)/(1+exp(\beta_0 +\beta_1 *x1+...+\beta_k *x_k)) \quad (2)$$

Further explanation will be provided along with the tables below.

In order to compare model fit, for each model, three types of 'Pseudo R-Squared' values are calculated and tabled. These include McFadden's, Maximum Likelihood and Cragg & Uhler's. These may be interpreted similarly to the R-Squared values in an OLS regression model. Essentially, these Pseudo R-Squared values represent the proportion of the variance in the outcome variable, retention that can be explained by the model.

Additionally, models were compared with the use of AIC (Aikaike Information Criterion) and BIC (Bayesian Information Criterion). Both AIC and SIB seek to address common issues associated with overfitting models by attaching a penalty term for the number of parameters included in the model. These measures attempt to address the balance between goodness of fit and model complexity to choose the most parsimonious model.

Results

This section will discuss the results from the nine models compared. First the three overall institutional models will be compared, followed by the nursing and non-nursing students, respectively. Explained variance, model fit, and significant predictors for each will be shared. Discussion of implications and future directions will follow.

Institutional models. The model using “Intake plus BSS Items” adds predictive power to the “Intake” model that approximates the “Year One” model. While the BSS model is more complex than the first year model, the true benefit lies in its ability to predict retention nearly a year sooner than we would otherwise be able to.

The three institutional models compared here show that at intake we are only able to account for approximately 11-18% of the variance in 15-month student retention, while at one year, we are able to explain 35-51% of the variance. This jump is to be expected considering at one year we are predicting something only three months away and based on more information. The model of interest, therefore is the BSS model because it allows us to explain 33-51% of the variance in 15-month retention, but is able to do so much earlier than the one year model. Table 2 below summarizes each of the models and is followed by a more detailed explanation of the models being compared. Table 3 below provides the explained variance terms for each of the models and is also explained further.

Table 2: Modeling Retention: Overall EC Models

	Intake	Intake plus BSS items	Year One
(Intercept)	0.01	1.78†	−1.59**
	(0.42)	(1.07)	(0.54)
GenderFEMALE	−0.21	−0.27	−0.22
	(0.27)	(0.35)	(0.32)
EthnicityAsian	−0.54	−1.55	−1.28
	(0.76)	(0.98)	(0.99)
EthnicityBlack	−0.48†	−0.30	0.40
	(0.26)	(0.32)	(0.32)
EthnicityUnknown or Other	−0.39	−0.26	0.01
	(0.32)	(0.40)	(0.39)
MilitaryActive	0.14	0.20	0.14
	(0.34)	(0.41)	(0.40)
MilitaryVeteran	−0.70†	−0.78†	−0.60
	(0.37)	(0.45)	(0.45)
LevelBaccalaureate	−0.28	−0.56	−0.92*
	(0.34)	(0.43)	(0.45)
DivisionCodeBU	−0.14	0.12	0.01
	(0.44)	(0.56)	(0.57)
DivisionCodeHS	0.61	16.07	1.48
	(0.96)	(560.16)	(1.07)
DivisionCodeLA	0.55	0.90	0.70
	(0.43)	(0.56)	(0.54)
DivisionCodeTE	0.17	0.43	0.45
	(0.50)	(0.65)	(0.60)
IncomeLevelBelow45K	0.01	0.19	−0.18
	(0.22)	(0.28)	(0.26)
EnglishLanguageNativeN	−0.00	0.20	−0.68
	(0.44)	(0.59)	(0.55)
FirstGenerationCollegeYes	0.13	0.35	0.47†
	(0.22)	(0.27)	(0.26)
FirstServiceEvaluation5-24	−0.01	0.05	−0.35
	(0.40)	(0.48)	(0.48)
FirstServiceEvaluation25-39	0.96**	1.28**	−0.15
	(0.37)	(0.46)	(0.49)
FirstServiceEvaluation40+	1.28**	1.90***	−0.67
	(0.43)	(0.56)	(0.67)
Q1.ECCourses		−0.61*	
		(0.31)	
Q1.ECExams		−0.11	
		(0.32)	
Q1.Transfer		−0.62*	
		(0.31)	
Q1.OtherExams		−0.17	

		(0.34)	
Q1.Portfolio		−0.49	
		(0.48)	
IntendedPace.Q2		−0.18	
		(0.18)	
PlannedTimeOff.Q3Yes		−0.04	
		(0.50)	
ExpectedTimeToCompletion.Q4		0.09	
		(0.06)	
PayConfidence.Q7Not Sure		−1.09*	
		(0.51)	
PayConfidence.Q7No		−0.34	
		(0.41)	
LastCollegeCourse.Q9In Past 5 Years		−1.02**	
		(0.37)	
LastCollegeCourse.Q95+ Years Ago		−0.44	
		(0.42)	
PreviousOnlineCourse.Q10Yes		−0.05	
		(0.29)	
PreviousCreditByExam.Q11Yes		0.89**	
		(0.33)	
f1.CollegePrep		−0.01	
		(0.04)	
f2.Motivation		0.01	
		(0.07)	
f3.CareerRelevance		−0.04	
		(0.06)	
ExpectedSalaryIncrease.Q21Yes		−0.54	
		(0.40)	
EC_GPA_1YR			0.45***
			(0.13)
ECHOURS_EARNED_COURSES_1YR			0.17**
			(0.06)
ECHOURS_EARNED_EXAMS_1YR			0.10***
			(0.03)
TRANSFER_HOURS_TOTAL_1YR			0.03**
			(0.01)
N	471	406	471
AIC	601.16	495.19	457.81
BIC	900.31	1072.11	823.44
$\log L$	−228.58	−103.60	−140.90

Standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 3: Explained Variance of Overall Models (Pseudo-R Squared Measures)

Model	McFadden	Max. Likelihood	Cragg & Uhler
Intake	0.11	0.14	0.18
Intake plus BSS	0.33	0.41	0.51
One Year	0.35	0.37	0.51

The first overall model, based on intake variables alone, explains only 11-18% of the variance in the outcome, retention. This essentially tells us that we aren't able to strongly predict retention based upon what we know about students when they begin with us. By comparison, the third overall model, based on intake plus first year variables, explains 35-51% of the variance in the outcome, retention. While still limited in its predictive ability, this is relatively strong for the social sciences. Remember, 100% explained variance would be indicative of a perfect 1:1 correlation based on which we can be certain of the outcome based on the predictors.

The second overall model, which is our model of interest because it includes just intake variables plus the BSS items, comes very close to the third model in terms of explained variances, with the pseudo R-squared values ranging from 33 to 51%. This is a good indicator that the BSS model has model fit that is comparable to that of the first year model.

Model selection also involves balancing model fit and model complexity. To address this, AIC and BIC can be compared across models to find the most parsimonious model. These measures are intended for comparison across models rather than in reference to a standard criterion. When looking across our models, we see that the AIC is reduced as (AIC=601) to the

AIC is based upon information entropy and is generally looking to identify how much information about our outcome is lost as we move to a less complex model. The lower AIC suggests a more parsimonious model. The BIC compared across models however increases between the intake model (BIC=900) and the BSS model (BIC=1072) and decreases again in the first year model (BIC=823). This is not surprising because the BIC carries a heavier penalty for the number of parameters in a model. While the first year model uses four additional predictors, the BSS model uses 18 additional variables to reach a comparable predictive strength.

The predictors, which met the criteria of 0.05 for statistical significance for each of the models, are listed in Table 4. Those with more credits on their First Service Evaluation were more likely to be retained at 15 months in both the "Intake" model as well as the "Intake plus BSS" model for the overall group. In the second model, four of the BSS items significantly predicting students' 15-month retention.

Table 4: Significant Predictors Across Models

Overall	Nursing	Non-Nursing
Intake Model	Intake Model	Intake Model
First Service Evaluation Credits	First Service Evaluation Credits Ethnicity: Uknown/Other Military Status: Veteran First Generation: Yes	First Service Evaluation Credits Military Status: Active
Intake Plus BSS	Intake Plus BSS	Intake Plus BSS
First Service Evaluation Credits EC Courses.Q1 Transfer.Q1 Pay Confidence.Q7 Last College Course.Q9 Previous Credit by Exam.Q11	First Service Evaluation Credits Ethnicity: Uknown/Other Military Status: Veteran First Generation: Yes EC Courses.Q1 Other Exams.Q1 Expected Time to Completion.Q4 Pay Confidence.Q7 Last College Course.Q9 Previous Online Course.Q10 Previous Credit by Exam.Q11 f3.Career Relevance	Transfer.Q1
One Year Model	One Year Model	One Year Model
EC GPA at 1 year EC Hours Earned by Courses 1 year EC Hours Earned by Exams 1 year Transfer Hours Total at 1 year	First Generation: Yes EC GPA at 1 year EC Hours Earned by Exams at 1 year Transfer Hours Total at 1 year	First Service Evaluation Credits EC GPA at 1 year EC Hours Earned by Courses at 1 year Transfer Hours Total at 1 year

Those planning to use courses towards degree completion were less likely to be retained than those who did not plan to. Once nursing and non-nursing students are assessed with separate models, it becomes clear that this finding holds true for nursing students, but not for non-nursing students. Those planning to use transfer credits towards degree completion were less likely to be retained than those

Students who were unsure that their payment sources would adequately cover their educational expenses were less likely to be retained than those that were confident. Interestingly, not being confident was not statistically different than those who were. A possible explanation may be that students that are unsure are still waiting for more information, possibly regarding financial aid, to help inform their decision to pursue a degree.

Students that had taken a college level course in the last 5 years compared with those who had never taken a college course were less likely to be retained. There was not a statistically significant difference between those that had taken a college course 5 or more years prior and those who had never taken a college level course. Those who had previous experience with a credit by exam program were more likely to be retained at 15 months than their peers. This is likely due to the large nursing student population overwhelming the overall model since nursing is the only school that has exam-based degrees.

The "One Year" model, first service evaluations are no longer statistically significant, but first year credit variables are statistically significant. For course-based, exam-based and transfer credits, students with more credits earned at 12 months were more likely to be retained at 15 months. The reference group for all of these measures is zero, which explains the much lower intercept in the 3rd model compared with the first two. Also, not surprisingly, those with a higher EC GPA at 12 months were more likely to be retained at 15 months.

Since Excelsior's School of Nursing is a rather large proportion of it's students, and the curriculum varies greatly, the same models were compared with nursing and non-nursing sub-populations. One critical distinction is that unlike our other degrees, our nursing degrees are largely exam-based rather than course-based. There are also group differences in military status. The nursing school has fewer active military students than our non-nursing students and a substantial proportion of those students are in fact active military. Due to these known group differences, the same three models were compared for each group.

Nursing models. The nursing model using "Intake plus BSS Items" adds predictive strength to the "Intake" model that actually surpasses the "Year One" model. The BSS model is once again more complex than the first year model, but the ability to predict retention earlier is worth this trade-off. The three nursing models compared here show that at intake we are only able to account for approximately 17-28% of the variance in 15-month student retention, while at one year, we are able to explain 38-55% of the variance. The model of interest, the BSS model, allows us to explain 45-64% of the variance in 15-month retention and is able to do so much earlier than the one year model. See Tables 4 and 5 for more detail.

Table 5: Modeling Retention: Nursing Models

	Intake	Intake plus BSS items	Year One
(Intercept)	−0.90	−0.31	−2.93***
	(0.61)	(2.06)	(0.80)
GenderFEMALE	−0.52	−1.06†	−0.50
	(0.41)	(0.60)	(0.47)
EthnicityAsian	−0.70	−2.31	−1.01
	(0.95)	(1.47)	(1.27)
EthnicityBlack	−0.43	0.38	0.76†
	(0.36)	(0.52)	(0.45)
EthnicityUnknown or Other	−1.08*	−1.29†	−0.35
	(0.50)	(0.73)	(0.60)
MilitaryActive	−0.15	−0.10	0.34
	(0.74)	(0.89)	(0.92)
MilitaryVeteran	−1.79*	−2.65**	−1.71*
	(0.73)	(0.90)	(0.80)
LevelBaccalaureate	−16.74	−17.44	−16.32
	(815.46)	(1135.76)	(846.28)
IncomeLevelBelow45K	0.01	0.08	−0.30
	(0.30)	(0.42)	(0.37)
EnglishLanguageNativeN	−0.15	0.49	−1.45†
	(0.57)	(0.86)	(0.76)
FirstGenerationCollegeYes	0.53†	1.20*	0.83*
	(0.31)	(0.47)	(0.38)
FirstServiceEvaluation5-24	1.26*	1.42*	−0.08
	(0.55)	(0.68)	(0.79)
FirstServiceEvaluation25-39	2.30***	3.02***	−0.59
	(0.54)	(0.68)	(1.00)
FirstServiceEvaluation40+	18.69	21.78	13.36
	(815.46)	(1135.76)	(846.29)

Q1.ECCourses		-1.25^{**}	
		(0.45)	
Q1.ECExams		0.99	
		(0.61)	
Q1.Transfer		-0.53	
		(0.60)	
Q1.OtherExams		-1.47^{*}	
		(0.67)	
Q1.Portfolio		1.19	
		(1.36)	
IntendedPace.Q2		0.02	
		(0.29)	
PlannedTimeOff.Q3Yes		-1.12	
		(0.94)	
ExpectedTimeToCompletion.Q4		0.30^{**}	
		(0.11)	
PayConfidence.Q7Not Sure		-2.94^{**}	
		(0.91)	
PayConfidence.Q7No		-0.90	
		(0.58)	
LastCollegeCourse.Q9In Past 5 Years		-1.62^{**}	
		(0.60)	
LastCollegeCourse.Q95+ Years Ago		-0.00	
		(0.71)	
PreviousOnlineCourse.Q10Yes		1.04^{*}	
		(0.48)	
PreviousCreditByExam.Q11Yes		1.54^{**}	
		(0.56)	
f1.CollegePrep		0.07	
		(0.06)	
f2.Motivation		0.09	
		(0.10)	
f3.CareerRelevance		-0.31^{*}	
		(0.13)	
ExpectedSalaryIncrease.Q21Yes		-1.45	
		(1.10)	
EC_GPA_1YR			0.48^{**}
			(0.18)
ECHOURS_EARNED_COURSES_1YR			0.17
			(0.14)
ECHOURS_EARNED_EXAMS_1YR			0.12^{***}
			(0.03)
TRANSFER_HOURS_TOTAL_1YR			0.10^{**}
			(0.03)
N	243	214	243
AIC	310.07	250.15	245.13
BIC	505.68	680.99	496.63
$\log L$	-99.04	2.93	-50.57

Standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 6: Explained Variance of Nursing Models (Pseudo-R Squared Measures)

Model	McFadden	Max. Likelihood	Cragg & Uhler
Intake	0.17	0.21	0.28
Intake plus BSS	0.45	0.51	0.64
One Year	0.38	0.42	0.55

Similar to the AIC and BIC comparisons for the overall models, model fit indicators behave similarly for the nursing population. When looking across our models, we see that the AIC is reduced as we move from the intake model (AIC=310) to the BSS model (AIC=250) to the first year model (AIC=245). The BIC compared across models however increases between the intake model (BIC=506) and the BSS model (BIC=681) and decreases again in the first year model (BIC=497). This is not surprising because, again, the BIC carries a heavier penalty for the number of parameters in a model.

The predictors, which met the criteria of 0.05 for statistical significance in the "Intake" model, are listed above in Table 4. Those with more credits on their First Service Evaluation were more likely to be retained at 15 months. The 'Unknown/Other' group for ethnicity was less likely to be retained than the reference group, which was 'White.' Veterans were less likely to be retained than civilians. Interestingly, first generation college students were more likely to be retained than their peers.

In the "Intake plus BSS" model as well, students with more credits on their First Service Evaluation were more likely to be retained at 15 months. Ethnicity is no longer significant, but military status and first generation college status still are. In addition, those planning to use courses towards degree completion were less likely to be retained than those who did not plan to and well as those planning to use credits from other (Non-EC) exams towards degree completion. These predictors speak to a misunderstanding students may have about expected program requirements. Unlike other degree programs at Excelsior, many of the nursing degrees are fairly proscriptive and exam-based so that students that don't anticipate their full workload to be Excelsior exams, may not be prepared for what the degree entails.

Additionally, students expecting to take longer to complete their degree were more likely to be retained at 15 months. This may also speak to realistic student expectations being a strength. Similar to the overall model, uncertainty about payment sources covering educational expenses predicts lower, while not being confident was not statistically significant.

Students that had taken a college level course in the last 5 years compared with those who had never taken a college course were less likely to be retained. Again, there was not a statistically significant difference between those that had taken a college course 5 or more years prior and those who had never taken a college level course. This is a surprising finding and will be discussed further below. Previous online coursework, as well as previous experience with credit-by exam, are associated with an increased likelihood of being retained. Unlike the overall models, and somewhat surprisingly, a higher score on the Career Relevance factor reduced one's likelihood of being retained.

In the third, "One Year", model, first service evaluations are no longer statistically significant, but first year credit variables are statistically significant including exam hours earned at one year, transfer hours earned and one year and EC GPA at one year. Compared with the overall model, this differs in that the EC course credits earned variable is no longer significant, which makes sense for our nursing students given the curriculum. The reference group for all of these measures is zero, which explains the much lower intercept in the 3rd model compared with the first two.

Non-nursing models. The three non-nursing models compared here show that at intake we are only able to account for approximately 12-19% of the variance in 15-month student retention, while at one year, we are able to explain 38-53% of the variance. This is consistent with what we would expect and with what we found overall and with nursing students. The BSS model allows us to explain 41-59% of the variance in 15-month retention and, as with the other student groups, this model is able to do so much earlier than the one year model. The BSS model explains more of the variance than the first year model for non-nursing students and does so earlier. See Tables 5 & 6 for more detail.

Table 7: Modeling Retention: Non-Nursing Models

	Intake	Intake plus BSS items	Year One
(Intercept)	2.35*	18.98	1.84
	(1.09)	(1182.81)	(1.29)
GenderFEMALE	−0.13	0.16	−0.15
	(0.37)	(0.55)	(0.46)
EthnicityAsian	−0.51	−3.03†	−1.85
	(1.33)	(1.81)	(1.69)
EthnicityBlack	−0.30	0.01	0.20
	(0.44)	(0.59)	(0.52)
EthnicityUnknown or Other	0.07	0.08	0.19
	(0.50)	(0.67)	(0.60)
MilitaryActive	0.88*	1.07†	0.99†
	(0.42)	(0.61)	(0.53)
MilitaryVeteran	0.20	0.62	0.53
	(0.50)	(0.72)	(0.64)
LevelBaccalaureate	0.25	0.06	−0.57
	(0.38)	(0.54)	(0.55)
IncomeLevelBelow45K	−0.13	0.04	−0.25
	(0.35)	(0.50)	(0.43)
EnglishLanguageNativeN	−0.14	−0.06	−0.58
	(0.87)	(1.19)	(0.97)
FirstGenerationCollegeYes	−0.07	0.24	0.37
	(0.34)	(0.45)	(0.41)
FirstServiceEvaluation5-24	−3.08**	−18.42	−4.15**
	(1.18)	(1182.81)	(1.42)
FirstServiceEvaluation25-39	−2.57*	−18.25	−4.36**
	(1.15)	(1182.81)	(1.51)
FirstServiceEvaluation40+	−1.79	−16.98	−4.57**
	(1.09)	(1182.81)	(1.57)

Q1.ECCourses		0.41	
		(0.94)	
Q1.ECExams		−0.10	
		(0.45)	
Q1.Transfer		−1.09*	
		(0.47)	
Q1.OtherExams		0.58	
		(0.54)	
Q1.Portfolio		−0.84	
		(0.58)	
IntendedPace.Q2		−0.52†	
		(0.30)	
PlannedTimeOff.Q3Yes		−0.47	
		(0.81)	
ExpectedTimeToCompletion.Q4		−0.08	
		(0.10)	
PayConfidence.Q7Not Sure		0.97	
		(1.17)	
PayConfidence.Q7No		−0.16	
		(0.96)	
LastCollegeCourse.Q9In Past 5 Years		−0.22	
		(0.62)	
LastCollegeCourse.Q95+ Years Ago		0.27	
		(0.68)	
PreviousOnlineCourse.Q10Yes		−0.56	
		(0.52)	
PreviousCreditByExam.Q11Yes		0.55	
		(0.54)	
f1.CollegePrep		0.01	
		(0.06)	
f2.Motivation		−0.12	
		(0.17)	
f3.CareerRelevance		0.02	
		(0.09)	
ExpectedSalaryIncrease.Q21Yes		0.04	
		(0.48)	
EC_GPA_1YR			0.45*
			(0.20)
ECHOURS_EARNED_COURSES_1YR			0.17*
			(0.08)
ECHOURS_EARNED_EXAMS_1YR			0.06
			(0.11)
TRANSFER_HOURS_TOTAL_1YR			0.03**
			(0.01)
N	228	192	228
AIC	274.53	229.62	208.61
BIC	466.57	646.58	455.52
$\log L$	−81.26	13.19	−32.30

Standard errors in parentheses

† significant at $p < .10$; *$p < .05$; **$p < .01$; ***$p < .001$

Table 8: Explained Variance of Non-Nursing Models (Pseudo-R Squared Measures)

Model	McFadden	Max. Likelihood	Cragg & Uhler
Intake	0.12	0.14	0.19
Intake plus BSS	0.41	0.45	0.59
One Year	0.38	0.38	0.53

Model fit indicators, AIC and BIC, tell a similar story for non-nursing students as with the earlier models. When looking across our models, we see that the AIC is reduced as we move from the intake model (AIC=275) to the BSS model (AIC=230) to the first year model (AIC=209). The BIC compared across models however increases between the intake model (BIC=467) and the BSS model (BIC=647) and decreases again in the first year model (BIC=456). This is consistent with what we found with the earlier comparisons.

The predictors, which met the criteria of 0.05 for statistical significance in the intake model, were First Service Evaluation credits, military status. Unlike the earlier comparisons, active military were more likely to be retained than civilians for non-nursing students. In the second model, neither of the above predictors were significant anymore after adding the BSS items and the only significant BSS predictor was the intention to apply transfer credits to the degree. These students were less likely to be retained.

The third model is consistent with earlier group comparisons. The significant predictors were First Service Evaluation credits, EC GPA at one year, EC hours earned by courses at one year, and transfer hours earned at one year. Compared with the overall models, EC credits earned by exam are no longer significant, which makes sense for our non-nursing students based on curriculum differences between divisions. Note that the standard error terms in the second non-nursing model, and particularly for the 'First Service Evaluation' and intercept are much higher than the others. This is likely due to the fact that the non-nursing students are a more heterogeneous group than the nursing students. There also tends to be a very wide range in number of credits transferred in between students.

Discussion

By including Beginning Student Survey items, we are able to approximate, and when analyzing nursing students separately, surpass the predictive ability we have at 12 months to explain variance in 15-month retention. Discussion of the model fit above illustrates that the BSS model is more complex, but this cost is reasonable considering the practical gain of earlier predictive ability. Essentially, the BSS provides new information about our students that uniquely contributes to their chances of being retained at 15 months and is able to provide that information early enough in a student's college career to influence intervention and outreach.

While the findings are encouraging, a limitation to this finding of course, is that the response rate for the BSS pilot was 34%. While this is a respectable response rate, it does leave us with much less information about the remaining 66% of our beginning students and leads to a concern of response bias. Response alone did not, however, predict retention, which was considered. This study included only 6 months of pilot data and it will be useful to see if using other data, as it becomes available, can validate the models. Also, the error terms in the non-nursing models limit the ability to use those variables are warning indicators. The models will need to be a work in progress in order to adapt to policy changes, student demographic changes, etc., and will continue to be improved over time. An additional limitation to this study is that it is very individualized to be appropriate to Excelsior College so the models and survey may look very different elsewhere.

A few intervention ideas are possible from this work that may lead to tangible benefits for students. One possibility is the use the logits from the logistic regression and based on the probabilities calculated, students could each be assigned a propensity score, which is essentially their likelihood of being retained or not. This score would range from 0 to 1 and could be used as a measure to flag at-risk students that may need some extra advisor time.

Another consideration is to use the findings to implement more targeted interventions. For example, if a student is flagged at-risk because they have low confidence in their prerequisite language and writing skills, they need a very different outreach than a student who is flagged because they have financial concerns about completing the degree or a lack of experience with online coursework. Perhaps we can get this type of data into the hands of advisors so that not only do they know whom to call, but they also know what type of assistance they may need.

Lastly, I'd like to know if the students intending to transfer in credits, but withdrawing, are actually going on to complete their degrees elsewhere. This question is also raised by the findings regarding previous college course experience predictors. A recent college course experience makes a student less likely to be retained compared with students who either don't have college course experience or those who have college course experience from five years ago or longer. Perhaps this indicates that some students are completing their degrees elsewhere, which we would like to know more about. When the opportunity arises to take a closer look at this, the National Student Clearinghouse data may be able to shed some light on this.

This study strongly supports the notion that a beginning student survey can improve predictive models empowering us to know more about our beginning students' likelihood to succeed and to know early enough in students' careers to intervene as needed. While other schools would need to develop their own institutionally relevant survey and predictive model, it would be valuable to see this replicated elsewhere.

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THE FALSE PROMISE OF NET PRICE AS AN AFFORDABILITY METRIC

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Abstract

Net price represents an institution's cost of attendance less grant aid received by students, and it has been heralded as the best available measure of affordability for colleges and universities. This promise, however, is overstated because the cost of living components that figure into net price calculations are ill-defined and unevenly calculated. This paper examines the variability in cost of attendance determinations and finds that 43.6% of all institutions fall outside of a $6,000 window centered on a county-level estimate for 9-month living costs. This wide variation in components of room and board, transportation, and other expenses for commuter students has been overlooked, and it confounds net price calculations to make net price a problematic metric to measure affordability or use in accountability systems.

Literature Review

Significant scholarly and public attention has focused on increases in sticker prices of colleges and universities (Kane, 2010; Baum & Ma, 2012), and the policy response has historically been to increase spending on student financial aid (Dynarski, 2002). As a principal funding mechanism for higher education in the United States, Federal Student Aid grant and loan programs delivered $137.6 billion to almost 14 million students (U.S. Dept. of Education, 2013). This equates to almost $10,000 per student receiving aid and approaches just under a third of the almost $500 billion spent on higher education annually.[1]

Distribution of these aid dollars based on the size of the gap between the total cost of attendance of their college or university, less an estimated contribution from the student and his or her family. The resulting amount to be paid by the student, or "net price," has gained traction

[1] In FY 2012, all higher education institutions spent just over $485 billion (Ginder & Kelly-Reid, 2013).

as more representative cost to families for a year of higher education than sticker price (Kelly, 2011). Net price figures prominently in the White House College Score Card as well as the watch lists published annually in the College Affordability and Transparency Center as required by the Higher Education Opportunity Act of 2008, and it is believed net price will be the metric used to gauge affordability for the Obama Administration's planned Postsecondary Education Rating System (PIRS).

Significantly less attention in the scholarly literature, however, has been paid to net price, with examinations providing large descriptive statistical overviews (Horn & Paslov, 2014), discussion of the net price calculators required by the Higher Education Opportunity Act (Fallon, M., 2011; Pope, 2011; Piccoli, 2012), and the watch lists also required by HEOA (Field & Newman, 2013). Very little work has been conducted on the actual components of cost of attendance beyond tuition and fees, in particular the cost of room and board and other expenses, especially for those living off campus. Rather, they are taken as a given. Notably, the Higher Education Act of 1965, as amended, explicitly states these expenses are "defined by the institution" (20 U.S. Code § 1087(ll) "Cost of attendance"). Even cursory evidence suggests institutions have adopted disparate and incomparable approaches this determination of costs. These disparities point to a need for research to answer important policy questions about how variation in determining living expenses that comprise costs of attendance and the resulting net price amount contributes to the equitable and optimal distribution of federal student aid dollars.

Methodology

The study principally relies upon data from the 2013 Integration Postsecondary Education Data System (IPEDS) Institutional Characteristics (IC) survey, and includes all institutions in the universe for which costs for full-time, first-time undergraduate students were reported for room and board expenses (not with family) and other expenses (not with family). Institutions in U.S. Territories and outlying areas were excluded because data to construct county-level estimates for living costs were generally unavailable. Two institutions classified as administrative units but still reported these charges were excluded, for a total of 6,438 institutions in the 50 United States and the District of Columbia (see Table 1 for a breakdown by sector). Among these, 4,130 institutions were "academic year reporters" – those institutions reported living costs and tuition for the academic year; the other 2,308 were "program reporters" – those reporting charges and costs by program. On the IPEDS IC survey, program reporters provide living costs for a 1-month (4-week) period which is then multiplied across the length of the program. These costs were normalized to nine months to compare to academic year reporters, and all costs in this paper are adjusted to reflect nine months.

As observed in a 2009 study from the Government Accountability Office in examining how estimated family contributions might be regionally adjusted, the principal challenge in comparing living costs is to adjust for regional and local variation. To control for these effects, county-level estimates for living expenses were generated for all institutions using an approach modeled on the on the MIT Living Wage Calculator (Glasmeier & Arete, 2014). Data were gathered independently from what is available in this online tool, however, and an effort was made to use resources that would have been available for building the living cost allowance budget for the 2013-14 academic year. In instances where county-level or more granular costs were unavailable, data were adjusted by the 2013 County Cost of Living Index (COLI) from the Council for Community and Economic Research to account for regional differences. This methodology is the same as used by Kelchen, Hosch & Goldrick-Rab (2014) and findings draw upon the same data set.

Estimates for Room & Board

U.S. Department of Housing and Urban Development 50th Percentile Rents for FY 2012 were the source for housing expenses. These data are collected and reported separately by county, and so regional adjustments are built into the data set. Values for a zero bedroom (efficiency) apartment are used for college cost of living estimates.[2]

U. S. Department of Agriculture Food Plans: Cost of Food for June 2012 were the source for food (board) expenses. The low-cost food plans for men and women ages 19-50 were averaged to arrive at a cost of $218 per month. This figure was adjusted by the county-level COLI to account for local variation in costs. The sum of food costs and housing costs added together represent the county-based estimate for room and board costs comparable to what institutions report in IPEDS.

Estimates for Other Expenses

Costs for transportation, health care, and miscellaneous expenses together comprise the estimate for expenses other than room and board. The 2012 Bureau of Labor Statistics Consumer Expenditure (CE) Survey for individuals under 25 years old (Table 1300) was the source for transportation expenses, costs for operation and maintenance of a car were used to estimate

[2] NASFAA (2013) issued guidance for financial aid officers that budgets for living expenses does not require living with roommates; only about 40% of institutions are NASFAA members.

student costs, but costs for capital outlay, and depreciation were not included. These amounts were $1,931 per year ($161 per month) for gasoline and motor oil and $1,322 per year ($110 per month) for other expenses such as financing, maintenance and repairs, license fees, etc. The CE Survey was also the source for miscellaneous expenses. Included in this category were personal care products and services at $372 per year ($31 per month), $249 per year ($21 per month) for fees and admissions, and $360 per year ($30 per month) for miscellaneous expenses. These amounts totaled to $981 annually or $82 per month.

Health care costs were estimated based on average per person costs for health insurance premiums by state in 2010 as compiled by the Kaiser Family Foundation. For the states for which data were unavailable (Alaska, Kansas, Nevada, Ohio, Oklahoma, and Texas) the national average of $215 was used but adjusted using the county-level COLI in those states only. Costs for actual out-of-pocket medical expenses were not included in estimates, nor were costs for child care or taxes.

Limitations and Caveats

A uniform method to estimate exact cost of living is elusive both because variation of potential costs at the individual level is wide within institutions as well as local geographic variation. Individuals who have higher health care costs or even basic child care costs will have higher expenses, although it may not be reasonable to account for such circumstances through professional judgment allowed to financial aid administrators under current regulations. While county-level estimates are superior to the College Board approach to estimate costs within 24 metropolitan statistical areas, variation in costs can still be wide within a county; in dense urban areas, rents can change dramatically over the span of a few blocks, although some expectation for commuting is reasonable.

Findings

The data already available in IPEDS show that for students not living with their families, the cost of living represents half (49.8%) across all institutions. These proportions do not decrease markedly for on-campus room and board costs, where such costs are applicable. Notably in the 2-year public sector where most community colleges are classified, and almost none have campus housing, more than two-thirds (70.5%) of the costs of attendance is simply living costs. Similarly, in the public 4-year sector, living costs represent 59.1% of the cost of attendance, indicating they exceed charges for tuition and required fees. Even in the sectors where cost of attendance is the highest and sticker prices regularly fall into the $25,000-$45,000 range, living costs average a third to just under a half of the total cost of attendance.

Table 1. Reported Living Costs (Not with Family) 2013-14 As Percent of Total Cost of Attendance

Sector	Institutions (N)	Not with family costs for room & board and other expenses as percent of total cost of attendance
4-year or above	**2,534**	**43.7**
Public	634	59.1
Private not-for-profit	1,200	35.6
Private for-profit	700	43.5
2-year	**2,109**	**57.8**
Public	1,019	70.5
Private not-for-profit	126	49.3
Private for-profit	962	45.4
Less-than 2-year	**1,797**	**48.9**
Public	228	58.8
Private not-for-profit	66	50.2
Private for-profit	1,503	47.3
Grand Total	6,438	49.8

Cost of attendance assumes in-state charges for tuition and fees when applicable.

Kelchen, Hosch and Goldrick-Rab (2014) summarized descriptive statistics for county-level estimates for living costs; tables 2 and 3 draw directly from this work. Highest costs were unsurprisingly in major metropolitan areas, especially in California and the North East. In fact, just over half of all institutions in the study (N=3,511) were located in the top quartile of counties by estimated cost of living. Living costs in this quartile ranged from $12,940 for total costs in Merced County, California, home of Merced College, to over $24,000 for institutions in the five boroughs of New York City. Suffolk County, where Boston, Massachusetts is located, for instance, has an estimated nine-month cost of living of $22,743; Los Angeles County's estimated nine-month cost of living is $18,144. The other half (48%) of institutions are located in counties in first three quartiles by living cost; variation in estimated cost of living was less than $4,000 from the minimum to the top of the 2nds quartile of counties. These costs ranged from a low of $9,126 in Randolph County, Arkansas, where Black River Technical College is located -- to just under $12,940 in Mohave County, Arizona, home of Mohave County Community College in Kingman.

Table 2. Summary of County-Level Cost of Living Estimates, 9 Months, All U.S. Counties*

	Room & Board Costs			Other Costs				
	Housing	Food	Total	Transp.	Health Care	Misc.	Total	Total
Min	2,862	1,665	4,572	2,061	1,224	621	4,077	9,126
25th pctile	3,969	1,872	5,877	2,331	1,809	702	4,860	10,863
50th pctile	4,662	1,944	6,606	2,421	1,890	729	5,040	11,678
75th pctile	5,623	2,068	7,711	2,565	2,025	774	5,371	12,940
Max	12,051	3,690	15,489	4,590	3,933	1,386	9,189	24,426
Mean	5,040	2,003	7,039	2,490	1,990	753	5,233	12,272
SD	1,572	214	1,719	266	457	80	682	2,213

* Includes only counties that have at least one higher education institution in the study population, county N =1,448; in Virginia, some of these geographical units are cities but treated as counties here.

Perhaps, most strikingly, while over half (56.4%) of institutions were found to report cost of living expenses within $3,000 above or below the county-level estimate, more than two out of every five institutions (43.6%) reported cost of living amounts that were outside of a $6,000 window centered on the county-level estimate. In many instances, institutions that were less than a mile apart reported living costs for nine months that were different by over $10,000. More institutions (32.8%) reported living costs more than $3,000 below the county-level estimate, while 10.8% reported living costs $3,000 or more above the county-level estimate.

Levels of variation differed by sector. Among public 4-year institutions, almost three quarters (71.6%) were within $3,000 of the county-level estimated cost of living, but only just over half (55.4%) of private, not-for profit 4-year institutions and 60.6% of private, for-profit institutions were within this range. In the two-year sector, almost two-thirds (63.2%) of public 2-year institutions reported living costs within $3,000 of the county-level estimate, and over half (53.1% and 58.5%) of private, not-for profit and for-profit institutions in this sector were within this range. In the less-than 2-year sector, which is dominated by smaller institutions that may have fewer resources to dedicate to research cost of living, less than half (45.3%) of institutions reported living costs within $3,000 of the county-based estimate. It is of course possible that the method used here for estimating cost of living at the county level produces estimates that are slightly high, but even if this were the case and a correction downward adopted, the same basic proportion of institutions would still fall outside of the +/- $3,000 range.

Table 3. Institutional Living Cost Allowances (over 9 months) for Off-Campus Students Compared to County-Level Living Cost Estimates, by Institutional Sector and Control

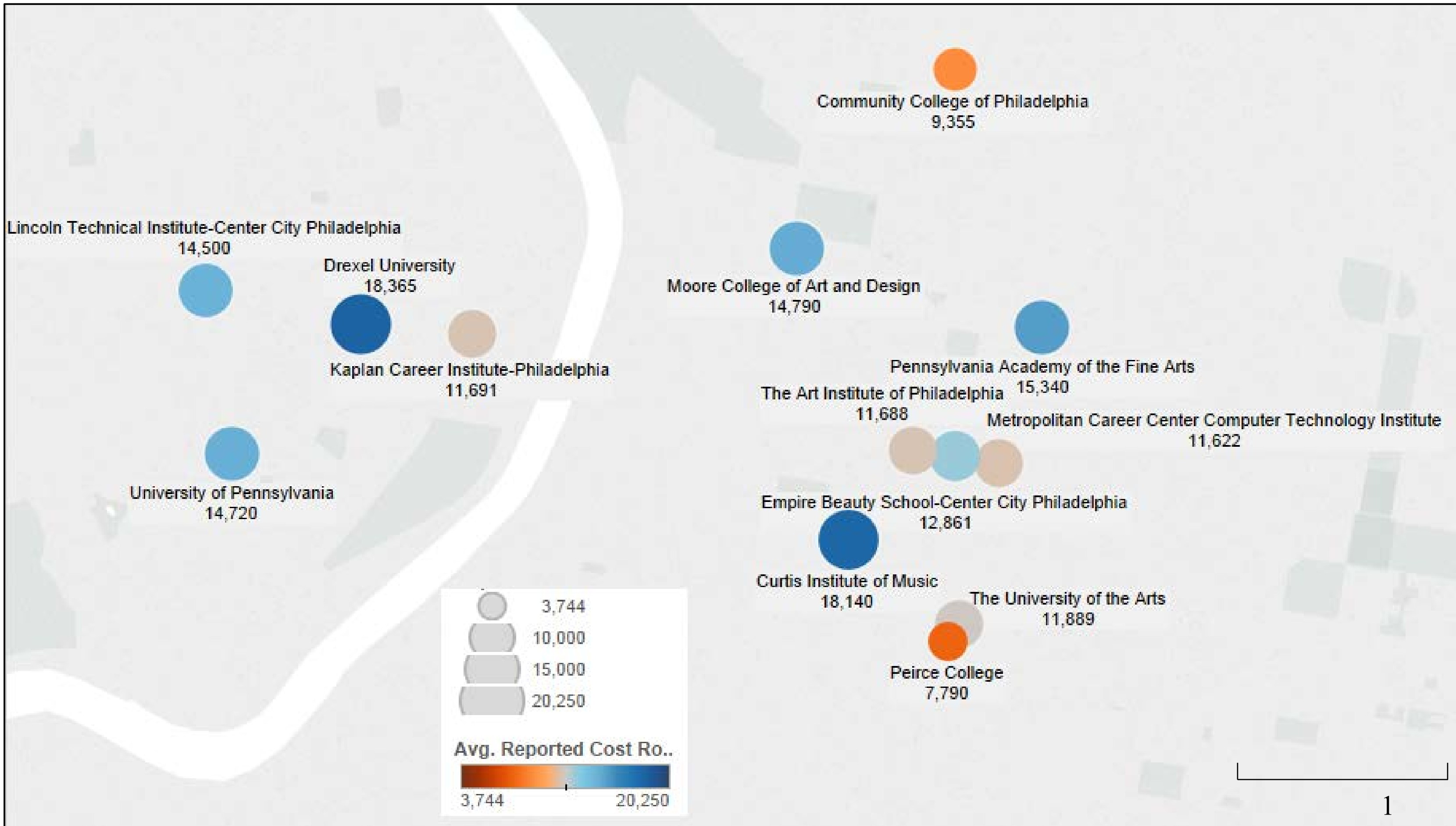
		Institutional Living Cost Allowance		
	Institutions	Above Estimate By $3,000+	Within $3,000 of Estimate	Below Estimate By $3,000+
Sector	N	Pct	Pct	Pct
4-year or above	**2,534**	**8.3**	**60.9**	**30.8**
Public	634	9.5	71.6	18.9
Private not-for-profit	1,200	7.8	55.4	36.8
Private for-profit	700	8.1	60.6	31.3
2-year	**2,109**	**10.1**	**60.4**	**29.5**
Public	1,019	7.7	63.2	29.1
Private not-for-profit	126	15.9	53.1	31.0
Private for-profit	962	11.9	58.5	29.6
Less-than 2-year	**1,797**	**15.1**	**45.3**	**39.6**
Public	228	14.0	40.8	45.2
Private not-for-profit	66	4.5	48.5	47.0
Private for-profit	1,503	15.8	45.8	38.4
Grand Total	**6,438**	**10.8**	**56.4**	**32.8**

Finally, differences in tightly defined geographic areas were stark. Given that the 2014 NEAIR Annual Conference is held in Philadelphia, the reported costs for Philadelphia County are presented here (see Table 4), but other geographic areas show similar levels of variation. The estimated living cost for the county were $16,020 for nine months, and among the 35 institutions in the county, just two institutions reported living costs more than $3,000 above this amount; these were La Salle University, where the reported costs were $20,250 for nine months and the National Massage Therapy Institute, where reported costs were $19,530 for nine months. Nineteen institutions reported living costs within $3,000 of the county-level estimate and fourteen institutions reported costs more than $3,000 below the county level estimate. The lowest of these was the LT International Beauty School $3,744 for nine months of living expenses, which is likely a reporting error, but the next two lowest institutions were Peirce College,

Table 4. Comparison of Living Cost Allowances to Estimated Living Costs, Philadelphia County

Institution Name	Allowance Reported By Institution: Room & Board	Other	Total	Estimated Living Cost	Reported - Estimated: Amount	Percent
La Salle University	16,200	4,050	20,250	16,020	4,230	26.4%
National Massage Therapy Institute	11,835	7,695	19,530	16,020	3,510	21.9%
Drexel University	14,415	3,950	18,365	16,020	2,345	14.6%
Curtis Institute of Music	13,000	5,140	18,140	16,020	2,120	13.2%
Temple University	11,410	5,790	17,200	16,020	1,180	7.4%
Jna Institute of Culinary Arts	12,550	4,600	17,150	16,020	1,130	7.1%
University of the Sciences	13,578	3,396	16,974	16,020	954	6.0%
Star Career Academy-Philadelphia	10,287	5,670	15,957	16,020	-63	-0.4%
Hussian School of Art	10,578	5,164	15,742	16,020	-278	-1.7%
Pennsylvania Academy of the Fine Arts	12,730	2,610	15,340	16,020	-680	-4.2%
Prism Career Institute-Philadelphia	9,549	5,265	14,814	16,020	-1,206	-7.5%
Orleans Technical Institute	9,549	5,265	14,814	16,020	-1,206	-7.5%
Moore College of Art and Design	12,790	2,000	14,790	16,020	-1,230	-7.7%
Saint Joseph's University	13,232	1,500	14,732	16,020	-1,288	-8.0%
University of Pennsylvania	12,922	1,798	14,720	16,020	-1,300	-8.1%
Lincoln Technical Inst-Ctr City Phila	9,342	5,157	14,500	16,020	-1,520	-9.5%
Lincoln Technical Inst-NE Philadelphia	9,342	5,157	14,499	16,020	-1,521	-9.5%
Lincoln Technical Inst-Philadelphia	9,342	5,157	14,499	16,020	-1,521	-9.5%
Philadelphia University	10,514	3,820	14,334	16,020	-1,686	-10.5%
Restaurant Sch at Walnut Hill College	9,825	4,350	14,175	16,020	-1,845	-11.5%
Aviation Inst of Maintenance-Phila	6,510	7,056	13,566	16,020	-2,454	-15.3%
Empire Beauty School-Ctr City Phila	6,174	6,687	12,861	16,020	-3,159	-19.7%
Empire Beauty School-NE Philadelphia	6,174	6,687	12,861	16,020	-3,159	-19.7%
Chestnut Hill College	9,008	3,100	12,108	16,020	-3,912	-24.4%
The University of the Arts	9,576	2,313	11,889	16,020	-4,131	-25.8%
ITT Technical Institute-Philadelphia	7,495	4,383	11,878	16,020	-4,142	-25.9%
Kaplan Career Institute-Philadelphia	5,607	6,084	11,691	16,020	-4,329	-27.0%
Kaplan Career Institute-Franklin Mills	5,607	6,084	11,691	16,020	-4,329	-27.0%
The Art Institute of Philadelphia	5,610	6,078	11,688	16,020	-4,332	-27.0%
Metropolitan Career Ctr CompTech Inst	7,427	4,195	11,622	16,020	-4,398	-27.5%
Jean Madeline Aveda Institute	6,993	4,176	11,169	16,020	-4,851	-30.3%
Holy Family University	8,872	1,290	10,162	16,020	-5,858	-36.6%
Community College of Philadelphia	6,660	2,695	9,355	16,020	-6,665	-41.6%
Peirce College	6,190	1,600	7,790	16,020	-8,230	-51.4%
L T International Beauty School	2,997	747	3,744	16,020	-12,276	-76.6%

Figure 1. Philadelphia Detail Map -- Reported Living Costs (Not with Family) for Nine Months, Selected Institutions



Estimated county-level cost of living for nine months: $16,020 reporting living expenses for nine months of just $7,790 and the Community College of Philadelphia, reporting living costs of $9,355. The detail map (Figure 1) perhaps best depicts how variation in this geographic region is not rationally distributed, and illustrates the underlying challenge to the validity of living costs as currently reported in IPEDS and used for the construction of financial aid budgets.

Discussion

What becomes clear from the data is net price is rendered unreliable as a way to measure colleges for maintaining affordability. For any college that has a substantial proportion of commuters, net price is substantively affected by a cost of living budget that may have been determined that is not comparable to other colleges. As we saw in the case of institutions in the Philadelphia area, variation in costs even in a tightly defined geographic is inexplicably wide, with a difference of over $16,000 between the highest and lowest reported cost of living budget for nine months in the county, but even within about one square mile in Philadelphia proper, costs varied by over $10,000 for nine months of living costs. Because cost of living comprises one third to two third of the cost of attendance budget and an even larger share of net price, once grant aid has been subtracted, any comparison of net price is more often measuring the cost of living attributed to commuting students.

Use of this measure to rate or rank colleges is even more problematic. The watch lists mandated by HEOA published in the College Affordability and Transparency Center are designed to flag outliers in net price, but the variation in cost of attendance described here, suggests these institution may be penalized for how they have determined their cost of living budgets. Further, once institutions turn attention to managing net price, the cost of living budget – as a significant and somewhat hidden component of net price becomes an easy way manage net price and game the system. Indeed, Kelchen, Hosch and Goldrick-Rab (2014) found that a sizable proportion of institutions dropped their cost of living budgets year to year for commuters, while rarely or never doing this for students living on-campus. Conversely rating or ranking systems that use net price, such as the *Washington Monthly* College Guide (2014) and *U.S. News & World Report'*s Best Value Schools (2014), may potentially flag outliers on the other tail of the distribution, again providing incentives to manage net price by underestimating cost of living expenses.

Such gaming has potential to harm students in multiple ways. Most obviously a net price figure communicated to consumers that is potentially thousands of dollars different from actually costs subverts the entire point of providing net price in the first place. Second, when institutions construct living cost budgets below what is realistic – and under-budgeting appears to be three times as prevalent as over-budgeting, students will qualify for less federal and state aid and may find that they do not have enough resources to meet basic expenses while pursuing their studies. At the very least, risk for financial issues to derail academic progress increases as a result of under-budgeting. Third, for students attending the one out of eleven institutions that reported cost of living expenses above the county-level estimates, borrowing exceed what is actually needed and contribute to unnecessary debt. It is also possible that the inflation of this cost of living budget prompts more federal or state grant aid than is needed to be awarded, thus reducing aid that other students might have received.

Recommendations

A number of potential policy solutions could correct or at least mitigate the problems with how cost of living budgets are constructed:

1) The federal government should either determine living costs, taking regional adjustments into account. While politically difficult, HUD fair market rents, military Basic Housing Allowance, and federal travel per diem allowances set precedence for such determination.
2) Absent a federally set amount, Reauthorization of the Higher Education Act should authorize the Secretary of Education to set a rigorous method to determine living costs.
3) Net price should not be included in federal ratings nor in third party rankings unless statistically adjusted to remove cost of living variation.

Regardless of the outcome of policy changes, some ancillary recommendations emerge for the short term and on an ongoing basis

4) Institutional researchers should examine cost of living in their local area, identify reported costs of other institutions in their area, and assist in budget construction
5) More research should be conducted to identify reasonable estimates for living expenses at geographic scales that make sense for colleges; particular attention should be placed on health care and transportation estimates
6) The research community should take a more active role in interrogating reliability and validity of educational statistics that gain national traction. As more political momentum gathers to identify measures for accountability and distribution of resources, policy must be informed by rigorously interrogated underlying data, and at present levels of error and anomalies in extant data sources remain relatively undocumented.

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TO BE, OR NOT TO BE A FULL-TIME STUDENT: THAT'S THE QUESTION

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Introduction

The image of the average college student continues to change, with only a quarter of students fitting the traditional profile of living and attending class on campus (Johnson & Rochkind, 2009). In addition to his/her schoolwork, a typical student experience now includes other responsibilities, such as working part- or full-time and having dependents. Forty-five percent of students in four-year schools work more than 20 hours a week; among community college students, 60% work more than 20 hours a week and 25% work more than 35 hours a week (Johnson & Rochkind, 2009). Almost a quarter of college students also have dependent children (Johnson & Rochkind, 2009). Also, attending class in a physical classroom with a professor is not as commonplace as it used to be. Nontraditional modes of study are increasingly popular, with the growth rate of online enrollments exceeding the growth of the overall higher education student population by almost elevenfold between 2003 and 2007 (Moore & Fetzner, 2009, p. 3).

Empire State College helps serve this growing nontraditional, adult population. The institution was founded in 1971 as a comprehensive college within the State University of New York system. The college's mission has been, and continues to be, to serve adult students who require alternatives to the traditional schedule associated with higher education. The typical Empire State College student is a busy adult with a job, family responsibilities, and a schedule that does not allow for a conventional college experience. Most students study part-time and are

New York State residents. The average age of an undergraduate student was 36 in the 2013-14 academic year.

With these changes comes the task of studying and understanding the factors that impact student success through this adult/nontraditional lens. Adult students possess diversity in terms of age, educational achievement, and economic, social and personal circumstances. These differences result in “patterns of educational engagement which are considerably different from younger students who stay on in full-time study after the age of 16” (McGivney, 2004, p. 33). In order to design effective programs and services to help nontraditional students reach their educational goals, information is needed on their enrollment patterns and the nature of their persistence problems (Choy, 2002, p. 2). Also, this type of research can help assist with early intervention plans, which are necessary to improve the persistence of adult students. This type of student is most likely to depart from college within his/her first year of enrollment; early intervention can help counteract this (Hardin, 2008, p. 51).

There is a unique trend at Empire State College where course completion rates are significantly lower when looking at students who take three or four four-credit courses during a term, as opposed to only one or two four-credit courses. Based on data from the past two full academic years (2011-12 and 2012-13), students who took one or two courses had completion rates of 89.7% and 84.7%, respectively. This percentage decreases significantly when looking at students who took three or four courses, with completion rates of 77.0% and 76.3%, respectively. This may be tied to the profile of the adult/nontraditional student, as outlined above. This research aims to explore different variables that may affect course completion rates for full-time students. These variables include: age, gender, new or continuing student status, online course participation, student motivation, employment status, marital status, and number of dependents.

Literature Review

The Nontraditional Student

Completion rates for both courses and programs are an important measure in higher education (Howell, Laws, & Lindsay, 2004, p. 243). Completion can be influenced by a variety of factors. In particular, degree completion rates are lower for part-time students, who are often older and financially independent (Taniguchi & Kaufman, 2005; Wasley, 2007; see also Chen & Carroll, 2007). Part-time students and adult students are more likely to have a variety of personal barriers, including competing responsibilities from work and children that can affect study time, financial insufficiency, a lack of academic preparation, and social and cultural issues (Brown, 2002; MacCann, Fogarty, & Roberts, 2012; Spellman, 2007). This can lead to certain behaviors, such as interrupted enrollment and excessive work hours, which may deter them from finishing their degrees (Berkner, He, & Cataldi, 2002; Carroll, 1989; Chen & Carroll, 2007; O'Toole, Stratton, & Wetzel, 2003). The student's first year is also critical. Nontraditional students are twice as likely to discontinue their studies in the first year when compared to traditional students (Horn & Carroll, 1996).

The chance of success in completing a degree based on the student's age is debated. "[Past] research has consistently shown that [adults] are less likely than younger students to complete a degree or certificate" (Calcagno, Crosta, Bailey, & Jenkins, 2007, p. 218; see also Choy, 2002; Choy & Premo, 1995). However, a study by Calcagno et al. suggests that, after controlling for cognitive mathematics ability, older students enrolled in Florida community colleges have a higher probability of completing a degree or certificate (2007, p. 218).

Responsibilities Outside of School

Other responsibilities, including having dependents, have a large impact on the success of the nontraditional student. Washington (2013) found a "significant negative relationship between the number of children one has and the highest level of education completed" (p. 19). Student parents face an increased likelihood of interrupting their studies (Holmes, 2005) due to conflicting role obligations (Van Rhijn, 2014, p. 1). While some studies have found no evidence that young children significantly lower their parents' college attainment (Horn, 1996; Jacobs & King, 2002; as cited in Taniguchi & Kaufman, 2005, p. 917), Taniguchi and Kaufman found that young children had a negative effect on women's degree completion. Parents also may have to pay for childcare while at work or in class, in addition to tuition and school-related expenses (Fairchild, 2003, p. 12). A lower income can increase a student's vulnerability to role conflict between simultaneous but incompatible demands (Home, 1998).

Home found that "multiple roles can increase feelings of confidence and self-esteem in adult women students… [but they] frequently experience strain as a result of time or resource constraints (1993; 1998; as cited in Kirby, Biever, Martinez, & Gómez, 2004, p. 66). Because role strain can increase stress and lead to abandoning studies, Merdinger found that women drop out more frequently than men for non-academic reasons (1991, as cited in Home, 1998).

Marriage can also affect student success. Family and marital change is a common barrier for students who do not complete their dissertation and/or drop out of college (Baird, 1997; Bowen, 1992; Burnett, 1999; Monaghan, 1989; as cited in Galvin, 2006, p. 420). O'Donnell states that approximately 45% of nontraditional students within the United States report being married or living with a partner, and 33% report being separated, divorced, or widowed, with 27% of these nontraditional students also being parents (2005, as cited in Galvin, 2006, p. 420).

Research indicates that “marital satisfaction affects academic completion rates and overall performance in academics, work environment, and sense of life satisfaction” (Galvin, 2006, p. 420; see also Busselen & Busselen, 1975; Kirby et al., 2004; Sori, Wetchler, Ray, & Niedner, 1996). Hanniford and Sagaria (2009) found that married students are less likely to finish a degree.

Family responsibilities can also be motivation for students. Multiple participants from the Van Rhijn study said that, “having a family made it easier to prioritize and avoid wasting time by maintaining focus on goals, even when stress was almost overwhelming” (2014, p. 6). Students felt pressure to finish quickly in order to limit the financial cost to their families. Some of the participants purposefully reduced their course loads to help balance their lives; some made a point to hand in assignments early, while others made an explicit choice to do less schoolwork or lower their achievement expectations in order to spend more time with family (Van Rhijn, 2014).

Employment can have both positive and negative effects on academic performance. Work time can crowd out study time, but can also teach students important work-environment and time management skills (Darolia, 2014). Pascarella and Terenzini (1991) reported that off-campus employment has a negative effect on persistence and bachelor’s degree attainment (as cited in Wohlgemuth et al., 2007, p. 462). Research has also found that longer working hours are associated with poorer study skills (Lammers, Onweugbuzie, & Slate, 2001), longer time to graduation (Canabal, 1998), and poorer academic performance (Di, 1996; Trockel, Barnes, & Egget, 2000) (as cited in Butler, 2007, p. 500).

The student’s perception of what his/her main role is may affect how much of an impact these additional work responsibilities have. Choy’s findings from the Beginning Postsecondary

Student's Longitudinal Studies (through the National Center for Education Statistics) found that two-thirds of nontraditional students considered themselves to be primarily employees, rather than students, and were likely to report that working has a negative effect on their grades (2002).

Motivation

Transitioning to higher education or back to higher education can be difficult for adult students because of the additional life pressures that they experience (O'Donnell & Tobbell, 2007). However, some of the same factors that serve as barriers to adult/nontraditional students can also serve as motivators. Motivation plays an essential role in learning by directing the student's behavior toward specific goals and improving performance (Singh, Singh, & Singh, 2011). Shields (1993) "found that…nontraditional students tend to be more intrinsically motivated [than traditional students]" (p. 357, as cited in Eppler, Carsen-Plentl, & Harju, 2000).

Other studies have found similar results. Distance education and nontraditional students tend to be more learning-goal oriented (or intrinsically motivated) and less performance-goal oriented (or externally motivated) than traditional students (Bennett, Evans, & Riedle, 2007; Williams & Williams, 2011). Bennett et al. (2007, p. 154) found that these learning-goal oriented students have been found to perform better academically than the performance-goal oriented students (see also Williams & Williams, 2011). Bennett et al. (2007) also found that nontraditional students spent the most time studying (see also Eppler & Harju, 1997).

Motivation is an especially important factor in influencing learning habits among students within an open education system; this type of student has been found to be low on personal aspiration (Singh, Singh, & Singh, 2012). In particular, poor motivation was identified as a factor contributing to high drop-out rates from online courses (Muilenberg & Berge, 2005, as cited in Singh et al., 2012).

Online Course Participation

In the 2013-14 academic year, approximately two-thirds of Empire State College students took at least one online course, while nearly one-half of students took all of their courses online. Research that compares online and traditional course completion rates is not conclusive (Howell et al., 2004). Completion rates for online courses are often believed to be lower than in traditional course delivery modes. Capan and Teclehaimanot's study on low online completion rates among community college students posed that some students have a "misguided impression that the coursework was easier [because] they do not have to physically report to a classroom and can do the work on their own time" (2013, p. 1464). However, the U.S. Department of Education concluded in 2009 that "students who took all or part of [a course] online performed better, on average, than those taking the same course through traditional face-to-face instruction" (Moore & Fetzner, 2009, p. 3). Levy states, "…the majority of literature (del Corral et al., 2006; Pérez-Prado & Thirunarayanan, 2002; Sharp & Cox, 2003; Xie et al., 2001) suggests, 'off-campus students did not suffer academically' (Sharp & Cox, 2003, p. 25)" (2009, p. 28). Research by del Corral et al. (2006) also indicated online students learned more (as cited in Levy, 2009, p. 28).

Distance education does raise issues in terms of access and retention (Burge, 1989; Garrison, 1989; as cited in Home, 1998). However, the flexibility and convenience of the online mode of study may attract nontraditional students, who are older and have work and/or family commitments. Nash found that this was the case, with distance learning students typically being older, part-time students, who often juggle a full-time job along with family responsibilities (Fjortoft, 1995; Galusha, 1997; Holmberg, 1995; McGivney, 2004; as cited in Nash, 2005). Choy (2002) found that moderately or highly nontraditional students were more likely to participate in distance education and to be in programs available entirely through distance education (see also National Survey of Student Engagement, 2008).

A study by Home (1998) found that the use of distance education eased the conflict that competing demands caused for female students. However, Ostman and Wagner found that "lack of time" was still the most commonly cited reason for dropping out offered by distance learners (1987; as cited in Nash, 2005). Garland also found "deeper" reasons for withdrawal, including poor direction and feedback on assignments and problems with time management (1993b; as cited in Nash, 2005).

Methodology

For reporting purposes, this study was split into three sub-studies. The analysis for each sub-study is based on registrations made by undergraduate students who took three or four four-credit courses in at least one term in academic year 2011-12 or 2012-13. A course completion was defined as any registration with grade of an A through a D- or a grade signifying credit. Chi square tests for independence were used for each sub-study to determine whether or not significant differences existed in completion rates between groups, and Cramer's V was used as a measure of effect size.

Sub-study #1: Student Characteristics

The goal of the first sub-study was to assess whether or not students with specific characteristics were better able to handle a full-time course load. Analyses were conducted to assess the impact of age, gender, new or continuing status, and online course participation on course completion rates.

Sub-study #2: Motivation

The goal of the second sub-study was to assess the impact of student motivation on full-time students' course completion rates. Four different variables were investigated in an attempt to approximate motivation: 1) time to degree plan approval, 2) application essay score, 3) whether or not a student attended a college information session, and 4) time to orientation. Only registrations made by students who met the criteria stated above with regard to the sample population and the following criteria were considered valid for this sub-study: 1) submitted only one application to Empire State College, 2) had an orientation date, 3) had a valid application score, and 4) had an approved degree plan date subsequent to their application date or no degree plan approval date.

Degree plan approval within one year. At Empire State College, undergraduate students design their own degree plan. Once complete, students submit their degree plan to the Office of College-wide Academic Review (OCAR) for approval. Students who had an approved degree plan in place within one year from their application date were designated as the "high" motivation group, and students who did not have an approved degree plan in place within one year from their application date were designated as the "low" motivation group.

Application essay score. Empire State College requires an undergraduate applicant to submit an essay, which is used to assess the writing skills of prospective students. The essays are scored by staff from the Office of Admissions using a rubric, which consists of five sections. Each of the five sections is scored from one to three. Approximately one-quarter of application essays reviewed by the Office of Admissions are assigned the maximum score of a 15. Students who earned an application essay score of 15 were designated as the "high" motivation group and students who were scored less than a 15 were designated as the "low" motivation group.

Attended a college information session. Empire State College offers college information sessions at locations across New York State. Students who attended an information session were designated as the "high" motivation group, and students who did not attend an information session were designated as the "low" motivation group.

Time to orientation. Prior to enrolling at Empire State College, matriculated students are required to submit an application and attend a general orientation. The top 25th percentile of students who moved the quickest from applying to attending orientation in comparison with other students in their center or program were designated as the "high" motivation group, while the lower 75th percentile of students in each center or program were designated as the "low" motivation group.

Sub-study #3: Work and Family

The goal of the third sub-study was to assess the impact of work and family commitments on full-time students' course completion rates. Specifically, analyses were conducted to assess the impact of employment status, marital status, and number of dependents on course completion rates. However, this information is not collected on the Empire State College Undergraduate Application. Therefore, data from the Federal Application for Student Aid (FAFSA) was used to ascertain students' marital status and number of dependents and to approximate employment status by using students' reported adjusted gross income (AGI). Only registrations made by students who met the criteria stated above with regard to the sample population and the following criteria were considered valid for this sub-study: 1) submitted a FAFSA to the college in at least one term in academic year 2011-12 or 2012-13 and 2) had an AGI of $0 or between $10,000 and $250,000.

Employment status. Students who had an AGI of $0 were considered "unemployed"; students with an AGI between $10,000 and $24,999 were considered "part-time"; and students with an AGI between $25,000 and $250,000 were considered "full-time."

Marital status. Students who reported on the FAFSA that they were single, separated, divorced, or widowed were considered "single," while students who reported that they were married or remarried were considered "married."

Number of dependents. Students who reported on the FAFSA that they had zero dependents made up the "no dependents" category, while students who reported that they had one or more dependents made up the "more than one dependent category."

Results

Sub-study #1: Student Characteristics

Age. There were significant differences ($p < 0.001$) in course completion rates between students in different age groups (Table 1).

Table 1

Course Completion by Age Group

Number of courses completed out of 3	Under 25 (N=2,781) n *(%)*	25-29 (N=2,637) n *(%)*	30-39 (N=3,967) n *(%)*	40-49 (N=2,611) n *(%)*	50+ (N=1,464) n *(%)*	χ^2	*V*
0 courses	482 *(17.3)* (4.5)	468 *(17.7)* (5.1)	603 *(15.2)* (1.2)	300 *(11.5)* (-5.0)	115 *(7.9)* (-7.8)	139.56***	0.06
1 courses	202 *(7.3)* (1.2)	182 *(6.9)* (0.3)	285 *(7.2)* (1.2)	174 *(6.7)* (-0.2)	68 *(4.6)* (-3.4)		
2 courses	327 *(11.8)* (0.8)	297 *(11.3)* (-0.2)	445 *(11.2)* (-0.3)	292 *(11.2)* (-0.3)	167 *(11.4)* (0.1)		
3 courses	1,770 *(63.6)* (-4.6)	1,690 *(64.1)* (-3.9)	2,634 *(66.4)* (-1.4)	1,845 *(70.7)* (4.1)	1,114 *(76.1)* (7.6)		

Number of courses completed out of 4	Under 25 (N=1,248) n *(%)*	25-29 (N=983) n *(%)*	30-39 (N=1,162) n *(%)*	40-49 (N=648) n *(%)*	50+ (N=287) n *(%)*	χ^2	*V*
0 courses	205 *(16.4)* (2.9)	168 *(17.1)* (3.1)	162 *(13.9)* (-0.1)	54 *(8.3)* (-4.5)	18 *(6.3)* (-3.9)	82.73***	0.07
1 courses	67 *(5.4)* (0.3)	57 *(5.8)* (0.9)	63 *(5.4)* (0.4)	30 *(4.6)* (-0.7)	9 *(3.1)* (-1.6)		
2 courses	86 *(6.9)* (2.0)	67 *(6.8)* (1.6)	59 *(5.1)* (-1.2)	26 *(4.0)* (-2.1)	11 *(3.8)* (-1.4)		
3 courses	122 *(9.8)* (-0.6)	118 *(12.0)* (2.1)	117 *(10.1)* (-0.2)	57 *(8.8)* (-1.3)	27 *(9.4)* (-0.5)		
4 courses	768 *(61.5)* (-2.9)	573 *(58.3)* (-4.9)	761 *(65.5)* (0.6)	481 *(74.2)* (5.4)	222 *(77.4)* (4.6)		

Note. *** = $p < 0.001$. Adjusted standardized residuals appear in parentheses below group frequencies and percentages.

Among students taking three courses in a term, 63.6% of "under 25" students completed all three courses, while 64.1% and 66.4% of students age "25-29" and "30-39" completed all courses, respectively. These course completion rates increased with age; 70.7% of students age "40-49" completed all three courses, and 76.1% of students "50+" completed all courses. The proportion of students completing zero out of three courses decreased with age. Over 15% of students in the youngest three age groups did not complete any of their three courses, while only 7.9% of students age "50+" completed none of their courses. There are similar results when students taking four courses in a term are considered. The proportion of students completing all of their courses increased overall with age; 61.5% of students "under 25" compared to 77.4% of students age “50+.” Again, smaller proportions of students in the older age groups completed zero out of four courses, compared to younger students. These results suggest that older student at ESC are better able to handle a full-time course load.

Gender. There were significant differences ($p < 0.001$) in course completion rates when comparing female and male students (Table 2).

Table 2

Course Completion by Gender

	Number of courses completed out of 3		Number of courses completed out of 4	
	Female (N=9,210)	Male (N=4,246)	Female (N=2,889)	Male (N=1,436)
	n *(%)*	n *(%)*	n *(%)*	n *(%)*
0 courses	1,253 *(13.6)* (-4.9)	714 *(16.8)* (4.9)	358 *(12.4)* (-4.4)	248 *(17.3)* (4.4)
1 courses	607 *(6.6)* (-1.3)	305 *(7.2)* (1.3)	141 *(4.9)* (-1.4)	85 *(5.9)* (1.4)
2 courses	1,033 *(11.2)* (-0.7)	494 *(11.6)* (0.7)	167 *(5.8)* (0.2)	81 *(5.6)* (-0.2)
3 courses	6,317 *(68.6)* (4.9)	2,733 *(64.4)* (-4.9)	287 *(9.9)* (-0.8)	154 *(10.7)* (0.8)
4 courses	-	-	1,936 *(67.0)* (4.3)	868 *(60.4)* (-4.3)
χ^2	30.16***		25.27***	
V	0.05		0.08	

Note. *** = $p < 0.001$. Adjusted standardized residuals appear in parentheses below group frequencies and percentages.

Among students taking three courses in a term, 68.6% of female students completed all three courses, compared to 64.4% of male students. A larger proportion of male students (16.8%) did not complete any of their courses, compared to female students (13.6%). There are similar results when students taking four courses in a term are considered, with the differences being slightly larger. Sixty-seven percent of female students completed all four of their courses, compared to 60.4% of male students, and a larger proportion of male students (17.3%) completed zero of their courses compared to female students (12.4%). This suggests that female students at ESC are slightly better at handling a full-time course load.

New or continuing status. There were significant differences ($p < 0.001$) in course completion rates when comparing students who were new and who were continuing in a term (Table 3).

Table 3

Course Completion by New or Continuing Status

	Number of courses completed out of 3		Number of courses completed out of 4	
	New (N=3,532)	Continuing (N=9,931)	New (N=1,018)	Continuing (N=3,310)
	n *(%)*	n *(%)*	n *(%)*	n *(%)*
0 courses	726 *(20.6)* (11.6)	1,242 *(12.5)* (-11.6)	218 *(21.4)* (7.8)	389 *(11.8)* (-7.8)
1 courses	302 *(8.6)* (4.9)	610 *(6.1)* (-4.9)	75 *(7.4)* (3.5)	151 *(4.6)* (-3.5)
2 courses	437 *(12.4)* (2.2)	1,091 *(11.0)* (-2.2)	53 *(5.2)* (-0.9)	196 *(5.9)* (0.9)
3 courses	2,067 *(58.5)* (-12.9)	6,988 *(70.4)* (12.9)	110 *(10.8)* (0.7)	331 *(10.0)* (-0.7)
4 courses	-	-	562 *(55.2)* (-7.3)	2,243 *(67.8)* (7.3)
χ^2	196.51***		83.69***	
V	0.12		0.14	

Note. *** = $p < 0.001$. Adjusted standardized residuals appear in parentheses below group frequencies and percentages.

Among students taking three courses in a term, 70.4% of continuing students completed all of their courses, compared to 58.5% of new students. A larger proportion of new students (20.6%) completed zero courses, compared to continuing students (12.5%). Similar results are seen when considering students who took four courses in a term. Continuing students completed all four courses at a rate of 67.8%, while 55.2% of new students completed all courses. Again, a larger proportion of new students (21.4%) completed zero courses, compared to continuing students (11.8%). These results suggest that continuing students are better able to handle a full-time course load.

Online education. There were significant differences ($p < 0.001$) in course completion rates when comparing the number of online courses taken by students in a term.

"All online" compared to "Not all online." The first part of this analysis compared students who took all of their three or four courses online to students who took did not take all online courses (Table 4).

Table 4

Course Completion for Students taking "All online courses" and "Not all online courses"

	Number of courses completed out of 3		Number of courses completed out of 4	
	All online (N=6,191)	Not all online (N=7,272)	All online (N=1,813)	Not all online (N=2,515)
	n *(%)*	n *(%)*	n *(%)*	n *(%)*
0 courses	1,099 *(17.8)* (9.5)	869 *(11.9)* (-9.5)	351 *(19.4)* (8.6)	256 *(10.2)* (-8.6)
1 courses	379 *(6.1)* (-2.8)	533 *(7.3)* (2.8)	86 *(4.7)* (-1.2)	140 *(5.6)* (1.2)
2 courses	576 *(9.3)* (-6.9)	952 *(13.1)* (6.9)	105 *(5.8)* (0.1)	144 *(5.7)* (-0.1)
3 courses	4,137 *(66.8)* (-1.0)	4,918 *(67.6)* (1.0)	176 *(9.7)* (-0.9)	265 *(10.5)* (0.9)
4 courses	-	-	1,095 *(60.4)* (-5.2)	1,710 *(68.0)* (5.2)
χ^2	126.79***		74.78 ***	
V	0.10		0.13	

Note. *** = $p < 0.001$. Adjusted standardized residuals appear in parentheses below group frequencies and percentages.

Among students taking three courses in a term, students who did not take all of their courses online completed all three courses at a slightly higher rate (67.6%) than students taking all of their courses online (66.8%). There is a larger difference when looking at the proportions of students who completed zero out of three courses – 17.8% of students taking all online courses compared to 11.9% of students who did not take all online courses. The results are similar, with larger differences, when considering students who took four courses. Students who took all of their courses online completed all four at a rate of 60.4%, compared to 68.0% of students who did not take all of their courses online. Again, a larger proportion of students who took all of their courses online completed none of their courses.

"At least one online course" compared to "Zero online courses." The second part of this analysis compared students who took at least one of their three or four courses online to students who took zero online courses (Table 5).

Table 5

Course Completion for Students taking "At least one online course" and "Zero online courses"

	Number of courses completed out of 3		Number of courses completed out of 4	
	At least one online (N=8,700)	Zero online (N=4,763)	At least one online (N=2,901)	Zero online (N=1,427)
	n *(%)*	n *(%)*	n *(%)*	n *(%)*
0 courses	1,412 *(16.2)* (7.2)	556 *(11.7)* (-7.2)	486 *(16.8)* (7.4)	121 *(8.5)* (-7.4)
1 courses	602 *(6.9)* (0.9)	310 *(6.5)* (-0.9)	160 *(5.5)* (1.2)	66 *(4.6)* (-1.2)
2 courses	925 *(10.6)* (-3.5)	603 *(12.7)* (3.5)	180 *(6.2)* (1.8)	69 *(4.8)* (-1.8)
3 courses	5,761 *(66.2)* (-3.5)	3,294 *(69.2)* (3.5)	305 *(10.5)* (1.0)	136 *(9.5)* (-1.0)
4 courses	-	-	1,770 *(61.0)* (-7.5)	1,035 *(72.5)* (7.5)
χ^2	59.59***		71.73***	
V	0.07		0.13	

Note. *** = $p < 0.001$. Adjusted standardized residuals appear in parentheses below group frequencies and percentages.

Among students taking three courses in a term, students who took zero online courses completed all three courses at a higher rate (69.2%) than students taking at least one of their courses online (66.2%). There is a larger difference when looking at the proportions of students who completed zero out of three courses – 16.2% of students taking at least one online course compared to 11.7% of students who took zero online courses. The results are similar, with larger differences, when considering students who took four courses. Students who took at least one of their courses online completed all four at a rate of 61.0%, compared to 72.5% of students who took zero online courses. Again, a larger proportion of students who took at least one of their courses online completed none of those courses.

Sub-study #2: Motivation

Degree plan approval within one year. There were significant differences ($p < 0.001$) in course completion rates for students who had an approved degree within one year of their application date, compared to students who did not have an approved degree within that time frame (Table 6).

Table 6

Course Completion based on Degree Plan Approval within One Year

	Number of courses completed out of 3		Number of courses completed out of 4	
	Approved (N=857)	Not approved within 1 yr (N=7,677)	Approved (N=415)	Not approved within 1 yr (N=2,290)
	n *(%)*	n *(%)*	n *(%)*	n *(%)*
0 courses	42 *(4.9)* (-9.7)	1,379 *(18.0)* (9.7)	14 *(3.4)* (-7.1)	386 *(16.9)* (7.1)
1 courses	32 *(3.7)* (-4.5)	613 *(8.0)* (4.5)	8 *(1.9)* (-3.5)	143 *(6.2)* (3.5)
2 courses	52 *(6.1)* (-5.4)	947 *(12.3)* (5.4)	14 *(3.4)* (-2.6)	155 *(6.8)* (2.6)
3 courses	731 *(85.3)* (13.6)	4,738 *(61.7)* (-13.6)	21 *(5.1)* (-3.9)	260 *(11.4)* (3.9)
4 courses	-	-	358 *(86.3)* (10.7)	1,346 *(58.8)* (-10.7)
χ^2	190.19***		116.93***	
V	0.15		0.21	

Note. *** = $p < 0.001$. Adjusted standardized residuals appear in parentheses below group frequencies and percentages.

Among students taking three courses in a term, 85.3% of students who had an approved degree within one year completed all of their courses, compared to 61.7% of students who did not have an approved degree within that timeframe. A greater proportion of students who did not have an approved degree within that year completed zero courses (18.0%), compared to students who did (4.9%). There are similar results when considering students who took four courses in a term. Among students who had an approved degree within one year, 86.3% completed all four courses, while 58.8% of students who did not have an approved degree within one year completed all of their courses. Again, a larger proportion of students who did not have an approved degree within one year completed zero out of four courses.

Application essay score. There were significant differences (*p* < 0.001) among students taking three courses in course completion rates when comparing students who scored a 15 out of 15 on their application essay to students who scored lower than a 15. There were not significant differences among students taking four courses (Table 7).

Table 7

Course Completion based on Application Essay Score

	Number of courses completed out of 3		Number of courses completed out of 4	
	15 (N=2,273)	Below 15 (N=6,261)	15 (N=727)	Below 15 (N=1,978)
	n *(%)*	n *(%)*	n *(%)*	n *(%)*
0 courses	331 *(14.6)* (-3.1)	1,090 *(17.4)* (3.1)	107 *(14.7)* (-0.1)	293 *(14.8)* (0.1)
1 courses	174 *(7.7)* (0.2)	471 *(7.5)* (-0.2)	43 *(5.9)* (0.5)	108 *(5.5)* (-0.5)
2 courses	232 *(10.2)* (-2.6)	767 *(12.3)* (2.6)	37 *(5.1)* (-1.5)	132 *(6.7)* (1.5)
3 courses	1,536 *(67.6)* (4.1)	3,933 *(62.8)* (-4.1)	66 *(9.1)* (-1.4)	215 *(10.9)* (1.4)
4 courses	-	-	474 *(65.2)* (1.4)	1,230 *(62.2)* (-1.4)
χ^2	20.00***		4.74#	
V	0.05			

Note. *** = *p* < 0.001, # = Results are not significant. Adjusted standardized residuals appear in parentheses below group frequencies and percentages.

Among students taking three courses, 67.6% of students who scored a 15 on their essays completed all of their courses, compared to 62.8% of students who scored below a 15. A larger proportion of students who scored lower than a 15 on their essays (17.4%) completed zero out of three courses, compared to students who scored a 15 (14.6%). Course completion rates were approximately equivalent for students taking four courses in a term, regardless of essay score.

Attended a college information session. There were significant differences in course completion rates when comparing students who attended an information session and students who did not for students taking three ($p < 0.001$) or four courses ($p < 0.01$) in a term (Table 8).

Table 8

Course Completion based on Attending Information Session

	Number of courses completed out of 3		Number of courses completed out of 4	
	Attended (N=2,220)	Did not attend (N=6,314)	Attended (N=627)	Did not attend (N=2,078)
	n *(%)*	n *(%)*	n *(%)*	n *(%)*
0 courses	289 *(13.0)* (-5.3)	1,132 *(17.9)* (5.3)	68 *(10.8)* (-3.2)	332 *(16.0)* (3.2)
1 courses	171 *(7.7)* (0.3)	474 *(7.5)* (-0.3)	28 *(4.5)* (-1.4)	123 *(5.9)* (1.4)
2 courses	269 *(12.1)* (0.7)	730 *(11.6)* (-0.7)	37 *(5.9)* (-0.4)	132 *(6.4)* (0.4)
3 courses	1,491 *(67.2)* (3.5)	3,978 *(63.0)* (-3.5)	64 *(10.2)* (-0.2)	217 *(10.4)* (0.2)
4 courses	-	-	430 *(68.6)* (3.3)	1,274 *(61.3)* (-3.3)
χ^2	28.74***		14.63**	
V	0.06		0.07	

Note. *** = $p < 0.001$, ** = $p < 0.01$. Adjusted standardized residuals appear in parentheses below group frequencies and percentages.

Among students taking three courses, 67.2% of those who attended an information session completed all of their courses, compared to 63.0% of students who did not attend a session. A larger proportion of students who did not attend an information session (17.9%) completed zero out of three courses, compared to students who did attend a session (13.0%). There are similar results when considering students who took four courses. Students who attended an information session completed all of their courses at a rate of 68.6%, while 61.3% of students who did not attend a session completed all courses. Again, a larger proportion of students who did not attend an information session (16.0%) completed zero out of four courses, compared to students who did attend a session (10.8%).

Time to orientation. Because the college has seven regional centers across New York State, as well as several other undergraduate programs, and each center or program has its own dean or director, the application, orientation, and registration processes differ across centers/programs. As a result, quartiles were calculated for each center/program, based on the students from that center/program and the time from their application date to their orientation date. The students in the top 25% at their center/program, in terms of moving in a timely fashion from applying to attending orientation, were compared to the bottom 75% at that center. The results of this analysis were not significant (Table 9).

Table 9

Course Completion based on Center/Program Quartile for Time to Orientation

	Number of courses completed out of 3		Number of courses completed out of 4	
	Top 25% (N=2,054)	Bottom 75% (N=6,480)	Top 25% (N=687)	Bottom 75% (N=2,018)
	n *(%)*	n *(%)*	n *(%)*	n *(%)*
0 courses	338 *(16.5)* (-0.3)	1,083 *(16.7)* (0.3)	88 *(12.8)* (-1.7)	312 *(15.5)* (1.7)
1 courses	170 *(8.3)* (1.4)	475 *(7.3)* (-1.4)	35 *(5.1)* (-0.6)	116 *(5.7)* (0.6)
2 courses	247 *(12.0)* (0.5)	752 *(11.6)* (-0.5)	40 *(5.8)* (-0.5)	129 *(6.4)* (0.5)
3 courses	1,299 *(63.2)* (-0.9)	4,170 *(64.4)* (0.9)	75 *(10.9)* (0.5)	206 *(10.2)* (-0.5)
4 courses	-	-	449 *(65.4)* (1.5)	1,255 *(62.2)* (-1.5)
χ^2	2.45#		4.16#	

Note. # = Results are not significant. Adjusted standardized residuals appear in parentheses below group frequencies and percentages.

Among students taking three or four courses, approximately equal proportions completed all of their courses, regardless of percentile grouping.

Motivation profile. The three significant variables (time to approved degree, application essay score, and information session attendance) were combined to create a "motivation profile." This was analyzed as a proxy for measuring student motivation. "Y-Y-Y," for example, is a profile that includes students who had an approved degree within one year, scored a 15 on their application essay, and attended an information session. "Y-N-N" is a profile that includes students who had an approved degree within one year, but scored below a 15 on their essay and did not attend an information session.

Students taking three courses. There were significant differences ($p < 0.001$) in course completion rates for the different student motivation profiles for students taking three courses (Table 10).

Table 10

Course Completion by Motivation Profile for Students Taking Three Courses
(Approved degree within one year – Score of 15 on application essay – Attended information session)

Number of courses completed out of 3	Motivation Profile: Y-Y-Y (N=101) n *(%)*	Y-Y-N (N=204) n *(%)*	Y-N-Y (N=142) n *(%)*	Y-N-N (N=410) n *(%)*	χ^2	*V*
0 courses	6 *(5.9)* (-2.9)	14 *(6.9)* (-3.8)	9 *(6.3)* (-3.3)	13 *(3.2)* (-7.5)	246.36***	0.10
1 courses	3 *(3.0)* (-1.8)	6 *(2.9)* (-2.5)	4 *(2.8)* (-2.2)	19 *(4.6)* (-2.3)		
2 courses	6 *(5.9)* (-1.8)	10 *(4.9)* (-3.1)	6 *(4.2)* (-2.8)	30 *(7.3)* (-2.8)		
3 courses	86 *(85.1)* (4.4)	174 *(85.3)* (6.4)	123 *(86.6)* (5.6)	348 *(84.9)* (9.0)		
Number of courses completed out of 3	**Motivation Profile: N-Y-Y (N=533) n *(%)***	**N-Y-N (N=1,435) n *(%)***	**N-N-Y (N=1,444) n *(%)***	**N-N-N (N=4,265) n *(%)***		
0 courses	75 *(14.1)* (-1.7)	236 *(16.4)* (-0.2)	199 *(13.8)* (-3.2)	869 *(20.4)* (9.2)		
1 courses	41 *(7.7)* (0.1)	124 *(8.6)* (1.7)	123 *(8.5)* (1.5)	325 *(7.6)* (0.2)		
2 courses	63 *(11.8)* (0.1)	153 *(10.7)* (-1.3)	194 *(13.4)* (2.2)	537 *(12.6)* (2.5)		
3 courses	354 *(66.4)* (1.2)	922 *(64.3)* (0.1)	928 *(64.3)* (0.2)	2,534 *(59.4)* (-9.0)		

Note. *** = $p < 0.001$. Adjusted standardized residuals appear in parentheses below group frequencies and percentages.

The motivation profiles that include students who had an approved degree within one year, or "primary Y" profiles (Y-Y-Y, Y-Y-N, Y-N-Y, Y-N-N) had higher proportions of students who completed all three courses, when compared to profiles that include students who did not have an approved degree within one year, or “primary N” profiles (N-Y-Y, N-Y-N, N-N-Y, N-N-N). Students who were “primary Y” completed all of their courses at least 85% of the time. Students who were “primary N” only completed all of their courses at a rate of 59.4%-66.4%. Students who were “primary N” also completed none of their courses at a rate of 13.8%-20.4%, compared to “primary Y” students who completed none of their courses at a rate of less than seven percent.

Theoretically if all three components of the motivation profile were of equal weight, the N-Y-Y profile would have a high proportion of students who completed all of their courses. However, only 66.4% of these students completed all three courses. When comparing the top four profiles in the table (“primary Y”) and bottom four profiles (“primary N”), the differences suggest that whether a student had an approved degree within one year of applying is the variable that carries the most weight.

Students taking four courses. There were significant differences ($p < 0.001$) in course completion rates for the different student motivation profiles for students taking four courses (Table 11).

Table 11

Course Completion by Motivation Profile for Students Taking Four Courses
(Approved degree within one year – Score of 15 on application essay – Attended information session)

Number of courses completed out of 4	Motivation Profile					
	Y-Y-Y (N=43)	Y-Y-N (N=85)	Y-N-Y (N=68)	Y-N-N (N=219)		
	n *(%)*	n *(%)*	n *(%)*	n *(%)*	χ^2	*V*
0 courses	1 *(2.3)* (-2.3)	1 *(1.2)* (-3.6)	1 *(1.5)* (-3.1)	11 *(5.0)* (-4.2)	147.54***	0.12
1 courses	1 *(2.3)* (-0.9)	3 *(3.5)* (-0.8)	0 *(0.0)* (-2.0)	4 *(1.8)* (-2.5)		
2 courses	0 *(0.0)* (-1.7)	3 *(3.5)* (-1.1)	0 *(0.0)* (-2.2)	11 *(5.0)* (-0.8)		
3 courses	4 *(9.3)* (-0.2)	6 *(7.1)* (-1.0)	2 *(2.9)* (-2.0)	9 *(4.1)* (-3.2)		
4 courses	37 *(86.0)* (3.2)	72 *(84.7)* (4.2)	65 *(95.6)* (5.6)	184 *(84.0)* (6.7)		

Number of courses completed out of 4	Motivation Profile			
	N-Y-Y (N=139)	N-Y-N (N=460)	N-N-Y (N=377)	N-N-N (N=1,314)
	n *(%)*	n *(%)*	n *(%)*	n *(%)*
0 courses	17 *(12.2)* (-0.9)	88 *(19.1)* (2.9)	49 *(13.0)* (-1.1)	232 *(17.7)* (4.1)
1 courses	8 *(5.8)* (0.1)	31 *(6.7)* (1.2)	19 *(5.0)* (-0.5)	85 *(6.5)* (2.0)
2 courses	6 *(4.3)* (-1.0)	28 *(6.1)* (-0.2)	31 *(8.2)* (1.7)	90 *(6.8)* (1.3)
3 courses	19 *(13.7)* (1.3)	37 *(8.0)* (-1.8)	39 *(10.3)* (0.0)	165 *(12.6)* (3.6)
4 courses	89 *(64.0)* (0.3)	276 *(60.0)* (-1.5)	239 *(63.4)* (0.2)	742 *(56.5)* (-6.8)

Note. *** = $p < 0.001$. Adjusted standardized residuals appear in parentheses below group frequencies and percentages.

These results mirror the analysis for students taking three courses. The motivation profiles that include students who were "primary Y" have higher proportions of students who completed all four courses, when compared to students who were "primary N." Students who were "primary Y" completed all of their courses at least 84% of the time. Students who were "primary N" only completed all of their courses at a rate of 56.5%-64.0%. Students who were "primary N" also completed none of their courses at a rate of 12.2%-19.1%, compared to "primary Y" students who completed none of their courses at a rate of five percent or less. Theoretically if all three components of the motivation profile were of equal weight, the N-Y-Y profile would have a high proportion of students who completed all of their courses. However, only 64.0% of these students completed all four courses. When comparing the top four profiles in the table ("primary Y") and bottom four profiles ("primary N"), the differences suggest that whether a student had an approved degree within one year of applying is the variable that carries the most weight.

Sub-study #3: Work and Family

Employment status. There were significant differences in course completion rates for students categorized as unemployed, part-time, and full-time employees who took three ($p < 0.001$) or four ($p < 0.01$) courses in a term (Table 12).

Table 12

Course Completion by Employment Status

	Number of courses completed out of 3			Number of courses completed out of 4		
	Unemployed (N=726)	Part-time (N=1,313)	Full-time (N=2,147)	Unemployed (N=213)	Part-time (N=329)	Full-time (N=609)
	n *(%)*	n *(%)*	n *(%)*	n *(%)*	n *(%)*	n *(%)*
0 courses	153 *(21.1)* (4.1)	239 *(18.2)* (2.6)	280 *(13.0)* (-5.4)	48 *(22.5)* (2.6)	52 *(15.8)* (-0.5)	91 *(14.9)* (-1.6)
1 courses	61 *(8.4)* (0.7)	126 *(9.6)* (2.9)	140 *(6.5)* (-3.2)	11 *(5.2)* (0.0)	24 *(7.3)* (2.1)	24 *(3.9)* (-1.9)
2 courses	115 *(15.8)* (2.8)	168 *(12.8)* (0.2)	247 *(11.5)* (-2.3)	17 *(8.0)* (1.9)	21 *(6.4)* (0.9)	24 *(3.9)* (-2.3)
3 courses	397 *(54.7)* (-5.4)	780 *(59.4)* (-3.7)	1,480 *(68.9)* (7.5)	22 *(10.3)* (-0.4)	30 *(9.1)* (-1.4)	76 *(12.5)* (1.6)
4 courses	-	-	-	115 *(54.0)* (-2.6)	202 *(61.4)* (-0.2)	394 *(64.7)* (2.2)
χ^2	68.00***			21.23**		
V	0.09			0.10		

Note. *** = $p < 0.001$, ** = $p < 0.01$. Adjusted standardized residuals appear in parentheses below group frequencies and percentages.

Students who were categorized as "full-time" employees and took three courses in a term completed all of their courses in that term at a rate of 68.9%, a significantly higher rate than students categorized as "unemployed" (54.7%) or a "part-time" employee (59.4%). More than 20% of "unemployed" students who took three courses in a term failed to complete any of their courses in that term, while "part-time" employees and "full-time" employees who took three courses in a term failed to complete any of their courses in that term at a rate of 18.2% and 13.0%, respectively. "Full-time" and "part-time" employees who took four courses in a term had comparable course completion rates, while "unemployed" students who took four courses in a term completed all of their courses in that term at a lower rate and failed to complete any of their courses in that term at a higher rate. These results suggest that students with an adjusted gross income between \$10,000 and \$250,000 handle a full-time course load better than students with an adjusted gross income of \$0.

Marital status. There were significant differences in course completion rates between single and married students who took three ($p < 0.001$) or four ($p < 0.01$) courses in a term (Table 13).

Table 13

Course Completion by Marital Status

	Number of courses completed out of 3		Number of courses completed out of 4	
	Single (N=2,793)	Married (N=1,393)	Single (N=757)	Married (N=394)
	n *(%)*	n *(%)*	n *(%)*	n *(%)*
0 courses	525 *(18.8)* (6.8)	147 *(10.6)* (-6.8)	147 *(19.4)* (3.6)	44 *(11.2)* (-3.6)
1 courses	238 *(8.5)* (2.4)	89 *(6.4)* (-2.4)	39 *(5.2)* (0.1)	20 *(5.1)* (-0.1)
2 courses	366 *(13.1)* (1.2)	164 *(11.8)* (-1.2)	41 *(5.4)* (0.1)	21 *(5.3)* (-0.1)
3 courses	1,664 *(59.6)* (-7.4)	993 *(71.3)* (7.4)	85 *(11.2)* (0.2)	43 *(10.9)* (-0.2)
4 courses	-	-	445 *(58.8)* (-2.9)	266 *(67.5)* (2.9)
χ^2	66.13***		13.86**	
V	0.13		0.11	

Note. *** = $p < 0.001$, ** = $p < 0.01$. Adjusted standardized residuals appear in parentheses below group frequencies and percentages.

Married students taking three or four courses in a term completed all of their courses in that term at a rate of 71.3% and 67.5%, respectively, while single students taking three or four courses in a term completed all of their courses in that term at a rate of 59.6% and 58.8%, respectively.

Nearly 20% of single students taking three or four courses in a term failed to complete any of their courses in that term, while married students taking three or four courses in a term failed to complete any of their courses in that term at a rate of 10.6% and 11.2%, respectively. These results suggest that married students handle a full-time course load better than single students.

Number of dependents. There were not significant differences in course completion rates between students with no dependents and students with one or more dependents who took three or four courses in a term (Table 14).

Table 14

Course Completion by Number of Dependents

	Number of courses completed out of 3		Number of courses completed out of 4	
	No dependents (N=1,767)	At least 1 dependent (N=2,419)	No dependents (N=606)	At least 1 dependent (N=545)
	n *(%)*	n *(%)*	n *(%)*	n *(%)*
0 courses	284 *(16.1)* (0.0)	388 *(16.0)* (0.0)	106 *(17.5)* (0.9)	85 *(15.6)* (-0.9)
1 courses	135 *(7.6)* (-0.4)	192 *(7.9)* (0.4)	25 *(4.1)* (-1.6)	34 *(6.2)* (1.6)
2 courses	235 *(13.3)* (1.1)	295 *(12.2)* (-1.1)	32 *(5.3)* (-0.2)	30 *(5.5)* (0.2)
3 courses	1,113 *(63.0)* (-0.6)	1,544 *(63.8)* (0.6)	66 *(10.9)* (-0.3)	62 *(11.4)* (0.3)
4 courses	-	-	377 *(62.2)* (0.3)	334 *(61.3)* (-0.3)
χ^2	1.21$^{\#}$		3.25$^{\#}$	

Note. # = Results are not significant. Adjusted standardized residuals appear in parentheses below group frequencies and percentages.

Students with no dependents taking three or four courses in a term had comparable course completion rates to students taking three or four courses with no dependents, indicating that having a dependent or multiple dependents does not impact a student's ability to handle a full-time course load.

Discussion and Implications

Student Characteristics

There were slight differences found between groups, based on student age, gender, and online course participation. The results suggest that older students and female students are better able to handle a full-time course load. While the literature on degree completion based on age is inconclusive, our results imply that our older students do not suffer academically. Within literature that explores the role of gender, there are oftentimes other contextual factors such as marital status and family life. Future research could include these additional cross-sections (divorced females vs. married females; the role of dependents; etc.) to further investigate these differences. While the research on online education is also inconclusive, our results suggest that students who take a greater number of online courses or all online courses have slightly lower completion rates than students who take fewer online courses or no online courses. The effect size of these variables was small to medium. Because of the large presence that online education has at Empire State College, this warrants further research to explore how our students' success might be affected by online courses.

There were larger differences between new and continuing students, with a small to medium effect size. A significantly greater proportion of continuing students completed all of their courses in a term, compared to new students. This strongly suggests that continuing students are better able to handle a full-time course load. Many of the variables that we analyzed, particularly new/continuing status, can help inform mentoring practices at our institution. These results can create guidelines that will help a mentor consider their student's characteristics and circumstances before recommending an appropriate course load.

Motivation

While there were slight differences when looking at information session attendance and application essay score (for students taking three courses), time to approved degree carried the most weight. When used in combination for the motivation profiles, the results suggest that time to approved degree was the only variable that had an impact. Profiles that included students who had an approved degree within one year of applying had significantly higher course completion rates when compared to students who did not have an approved degree within one year. The combination of the other two variables did not appear to have an effect.

The one drawback of using the variable of whether or not a student has an approved degree plan within one year to assess student risk is that it takes an entire year to ascertain this information. This is problematic because as Horn and Carroll (1996) state, nontraditional students are much more likely to drop-out in their first year than traditional students. Text mining of application essays is an alternative method for approximating motivation worthy of exploration. It has the benefit of being available prior to a student's first registration. Perhaps over time, an index of key words associated with student achievement or motivation could be developed. For example, if a student used the word "promotion" or "raise," in their application essay they might be considered to have more incentive or motivation than an average student.

Work and Family

Prior to determining whether to use students' FAFSA information for the third sub-study on the impact of work and family, we attempted to use data collected from Empire State College students who responded to the spring 2014 administration of the National Survey of Student Engagement (NSSE). Data from the survey item asking how many hours per week students spend working off campus was paired with registration data for students who took three or four four-credit courses during the college's spring 2014 term.

Among students who took three courses, those who stated on the survey that they worked 30 or more hours per week completed all of their courses at a rate of 83.3% and none of their courses at a rate of 1.9%, while students who stated on the survey that they worked fewer than 30 hours per week completed all of their courses at a rate of 86.8% and none of their courses at a rate of 2.9%. Among students who took four courses, those who stated on the survey that they worked 30 or more hours per week completed all of their courses at a rate of 83.3%, while students who stated on the survey that they worked fewer than 30 hours per week completed all of their courses at a rate of 83.9%. No students in either group failed to complete any courses. Group differences were not statistically significant for students taking three (χ^2 (3, N=122) = 0.82, p=0.84) or four courses (χ^2 (3, N=43) = 3.13, p=0.37).

Because the percentage of NSSE respondents who completed all of their courses was extremely high for both groups, we conducted a follow up study comparing NSSE respondents' completion rates to the completion rates of all other students enrolled in the spring 2014 term with comparable course loads. NSSE respondents who took three or four courses in that term completed all of their courses at a rate of 85.2% and 83.7%, respectively, while all other students who took three or four courses in that term completed all of their courses at a rate of 65.3% and 61.6%, respectively. Group differences were statistically significant for students taking three (χ^2 (3, N=2,563) = 22.65, $p < 0.01$) or four courses (χ^2 (3, N=43) = 3.13, p=0.37). Based on this information, we concluded that NSSE respondents were not a representative sample of the entire student population and that an alternative methodology to measure the impact of work and family on course completion rates needed to be considered.

Survey data can be used for multiple purposes (e.g., advertising, policy changes); however it is important to keep in mind that survey respondents are not necessarily representative of the college's entire student population and that generalizing survey findings can be problematic. If a college plans to use survey findings to make decisions affecting academic or student service policies, it is important to conduct a preliminary analysis to ensure the presence of an unbiased or representative sample.

There were slight differences based on employment and marital status. Students designated as "employed" completed a higher percentage of their courses than "unemployed" students and "married" students handled a full-time course load better than their "single" counterparts. No differences were observed based on whether or not students had any dependents. The slight differences based on employment status were most likely due to socioeconomic factors, and this study provides no evidence that classifying students based on their adjusted gross income is a valid method for approximating employment status.

With the amount of existing literature stating that the success of adult students can be heavily influenced by work and family responsibilities, Empire State College needs to find a systematic method for capturing this data. One possibility is to ask prospective students to provide this information on the application. Another method is to ask students to update their demographic information as part of the registration process each term. This would provide up-to-date information on students and allow college staff to determine whether or not changes in employment status, marital status, or number of dependents serve as predictors of student risk.

In conclusion, this study provided some valuable insight on students who are equipped to handle a full-time course load. It also highlights the need for Empire State College to refine or implement processes to collect student data that existing literature states can impact nontraditional students' college experience. As more student data becomes available, student risk models, which produce scores designed to trigger intervention or remediation strategies, can be developed with the ultimate goal of improving course and degree completion rates across the college.

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