PERSISTENCE IMPACTS ON STUDENT SUBGROUPS THAT PARTICIPATE

IN THE HIGH IMPACT PRACTICE OF SERVICE LEARNING

by

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ABSTRACT

Persistence Impacts on Student Subgroups that Participate in the High Impact Practice of Service Learning

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Sustained student success in higher education requires institutional leaders to properly use limited resources for activities and programs intended to improve rates of persistence and reduce graduation timelines. Consequently, educational leaders are challenged to determine what curricular and co-curricular programs affect student success outcomes—both positively and negatively.

The purpose of this study was to assess the impacts of qualified service learning courses on student persistence. The study research questions, and methods of analysis, were designed to inform local academic stakeholders of the impacts their curricular decisions had on student success and persistence outcomes. Relying on Astin and Antonio’s inputs, environment, and outputs (IEO) conceptual model to structure a quasi-experimental research methodology, this study examined the treatment impacts of persistence on participating students when compared to their counterparts.

Historical undergraduate student-level data used for this analysis were drawn from 3 years/6 terms of students enrolled in 254 courses that followed an approved service learning curriculum. Control groups of students available for analysis were taken from students who opted not to take service learning courses (N = 108,338). The final sample of analyzed student participants available for this study encompassed N = 8,959; n = 8,948 of them were successfully matched with control students to determine comparison outcome results.

The research outcomes complement prior student success research on the high impact practice of service learning. The results of this study demonstrated a positive return on investments, as measured by retained tuition, to local administrators at Utah State University. Implications for practice suggest the importance of assessing generalizable and broadly accepted curriculum and instruction for its impacts on local student bodies and their subgroups.

(209 pages)

PUBLIC ABSTRACT

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The university focuses on student-centered learning experiences and encourages student success through engagement and discovery. Departments and programs within universities are organized to support this mission. A major part of encouraging engagement is retaining students and helping them persist towards earning their academic degrees. Likewise, campus initiatives, resources, and activities are intended to support these same goals.

This research investigated the impacts of service learning courses on student persistence to the next term. The research methods used for this study were intended to provide leaders of higher education with valid and reliable information about activities that contribute to or inhibit student success. The research findings complement prior student success research on the high impact practice of service learning. The results demonstrate that when Utah State University students who participate in service learning courses are compared to their counterparts, who did not participate, they are more likely to re-enroll the following term. The results also show differing outcomes of persistence on subgroup populations of students during various academic terms. The implications of the study results provide information to local educational administrators of the impacts on their student body resulting from their curriculum design, development, and implementation of service learning courses.

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John Louviere

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CHAPTER I

INTRODUCTION

“Higher education impacts virtually every facet of our society and, with the ever-increasing focus on a knowledge-based economy, has become even more essential to the productivity of our lives” (Freedman, 2017, p. v). For individuals, education provides for the American dream, which relies on social mobility. Without proper education, history illustrates this social success increases for individuals with greater financial capacity (Bourdieu, 1974) and “getting ahead and getting an education are inseparable in the minds of most Americans” (Labaree, 1997, p. 1).

Although higher education provides individual graduates with a better quality of life, producing people with the knowledge, skills, and attitudes to create innovative products and services is an essential component of the U.S. as a premier competitor in the global marketplace. As such, government is expected to cultivate a strong society and economy through an educational system (Topper & Howard, 2017). In 1963, Clark Kerr, former Chancellor of the University of California at Berkley, explained that a critical role of a university is to create new knowledge which is “the most important factor in economic and social growth” (Kerr, 2001, p. xii). Tinto (2012) carried forward Kerr’s sentiment and emphasized that publicly funded universities should create both new knowledge to spur economic innovation and socially useful and economically productive credentialed individuals.

From the outset of the nation, public leadership developed institutions and educational programs to promote and sustain economical growth and social wellbeing. As early as 1636, American educational organizations were innovatively adapting to support economies of the time. John Harvard seeded what was to become America’s first college, with nine colonial colleges established in the following 100 years. States were encouraged to create their own higher education institutions and, by the start of the Civil War, over 250 institutions had begun (Carey, 2016; Freedman, 2017). In 1862, vocational programming in American education was formalized through the Morrill Act, integrating academic and vocational curricula by establishing land grant universities (Jencks & Riesman, 1968). The primary objective of these new universities was to not "exclude other scientific or classical studies, [but] to teach such branches of learning as are related to agriculture and the mechanic arts" (Bok, 2006, p. 26). Growing federal support for higher education is illustrated by legislation such as the Hatch Act in 1887, which created agricultural experimentation stations, and the Smith-Lever Act of 1914, establishing agricultural extension services. By World War II, public universities provided a variety of breadth liberal arts and vocational programs to Americans. In this era, the federal government catalyzed a rapid change in higher education by providing substantial financial resources in the Servicemen's Readjustment Act of 1944 (commonly known as the G.I. Bill). The Bill introduced seismic waves of change that drastically affected how the nation's colleges and universities operated (Bok, 2006).

Addressing historical change in higher education, Christensen and Eyring (2011) wrote, "American universities rose to preeminence by voluntarily embracing innovation. They changed when the great European universities of the day did not. Innovation was not a defensive reaction but a strategy for success" (p. 396). Throughout time, university leaders strategically responded to evolving societal demands and modified their breadth and focus ranging from liberal academic disciplines to skill-based workforce training. In 2007, Utah, along with other states, experienced a recession that catalyzed higher education administrators to again rethink the way they operate in order to sustain an accelerating rate of change to meet the needs of their students, resulting in financial incentives through performance-based funding. Governing bodies have questioned whether higher education's curricular and co-curricular strategies were a valued public good (Pasque, 2006) and have increased levels of scrutiny used to measure institutional success (Taylor

& Massey, 1996). "Institutions that cannot adapt face mergers, acquisitions, or even closure if they cannot remain viable" (Hanover Research Council, 2019, p. 1).

The intent of this study was to discover the effects of intentionally designed activities on student retention outcomes, measured by persistence. The methods used for this study make it possible to compare students who voluntarily participate in activities with students who do not. Using learning analytics, it was possible to isolate the activity as the only differentiating variable between the two compared groups (those who participated and those who did not) and measure its effects on student outcomes. Because the student activities were voluntary, self-selection bias could have skewed outcome results, and this presented one of the primary challenges in the research methodology. Self-selection bias was addressed by employing extensive statistical procedures and learning analytics to match students with similar individual characteristics and backgrounds. This matching method made it possible to confidently compare outcome differences without concern that self-selection was influencing the results.

Academic and political leaders advocate for evaluation methods, like those used for this study, to provide defensible insights into the impact of public funding on student outcomes (Astin & Antonio, 2012; Campbell, Mata, & Galloway, 2017; National Conference of State Legislatures [NCLS], 2014; Ward, 2018). In addition, public officials and educational leaders have been challenged to demonstrate the effectiveness of the funding on individuals, society, and local economies (Palmer, 2012). In the absence of timely assessment, educational leaders make delayed decisions based on postmortem data from national or local student surveys, annual rates of retention, or longer-term graduation rates. These delayed decisions are most often at the institutional level and are inadequate as they "do not represent student performance in specific classes or in response to assignments crafted by individual faculty; unfortunate, considering that assignment design is an especially powerful way to improve student performance" (Maki, 2017, p. x).

In support of the accountability demands placed on educational leadership, this study employed methods and tools intended to provide higher education institutions with valid and reliable information about activities that contribute to or inhibit student success. Additionally, the research methods employed for this study can be used to estimate financial impacts that curricular and co-curricular activities have on institutional and student success.

Student Success in Higher Education

Measuring Student Success

Scholars from a variety of disciplines have strived to understand how students succeed in higher education. Even defining student success varies by institution and often uses individual-level measurable indicators. Common indicators used by institutions to measure student success include enrollments, grades, and retention and graduation rates (Venezia, Callan, Finney, Kirst, & Usdan, 2005). Other traditional metrics may include individual academic achievements such as credit hours earned, admission to graduate programs, and performance on professional exams, e.g., PRAXIS for education or CPA tests for accountancy (Astin & Antonio, 2012; Kuh, Kinzie, Buckley, Bridges, & Hayek, 2006). To further understand what leads to student success in higher education, researchers have used behavioral and latent metrics such as, "academic achievement, engagement in educationally purposeful activities, satisfaction, persistence, attainment of educational objectives, and acquisition of desired learning outcomes that prepare one to live an economically self-sufficient, civically responsible, and rewarding life" (Kuh, O'Donnell, & Schneider, 2017, p. 9).

In the literature, a wide variety of metrics are used to explain student success and outcome measures, and the metrics differ from one research study to another. For example, Seidman (2012) provided a broad and holistic definition of student success by stating, "Student success [is] attainment of academic and/or personal goal(s). A student may attain academic and/or personal goals prior to graduation or may graduate without meeting those goals" (p. 270). This definition holistically captures an individual's perspective of student success. However, when using these broad and subjective outcomes, it is difficult to make operational judgements on impacts that university activities have on student success. Yukl (1989) provided a dated, yet pertinent leadership strategy for successfully evaluating system-wide initiatives. He emphasized that effective analysis requires clear and precise communication of expectations and outcomes. Following his recommendations, it is necessary to utilize interpretable outcome indicators so that stakeholders can determine whether the design and delivery of their initiatives contributes to student success.

Student Persistence in Higher Education

Student retention rate is a prominently accepted metric found in the literature and is often used for institutional goal setting and performance (Bean & Vesper, 1992; Radford, Berkner, Wheeless, & Shepherd, 2010). The terms retention and persistence are often used interchangeably in the literature to describe a student's behavior to stay enrolled over a term-based timeframe. Kuh et al. (2006) provided a comprehensive review of student success research literature and stated, "The most often cited theories define student success in college as persistence and educational attainment" (p. 11). Student persistence will be the outcome measure used for this study.

The effort to understand rates of institutional retention and individual student persistence have led to a substantial amount of research focused on explaining student performance and behavioral outcomes (Kinzie & Kuh, 2017; Pascarella & Terenzini, 2005; Seidman, 2018). Recently, researchers have used advanced statistical techniques and theoretical frameworks to estimate the effects of university activities on student persistence and degree completion. Term-to-term persistence, as a student outcomes metric, becomes a useful and timely indicator demonstrating a student's abilities and commitment to stay in college (Kuh et al., 2006). Once an institution can confidently measure a student's level of persistence, it can then evaluate the effectiveness of university activities.

High Impact Practice Activities

In 2005, the Association of American Colleges and Universities (AAC&U) released a 10-year Liberal Education and America's Promise (LEAP) initiative identifying essential learning outcomes that prepare students for the "new global century" (Kuh, 2013, p. v). The initiative's intent was to "give students a compass to guide their learning, and to make the aims and outcomes of a liberal education…the expected framework for excellence at all levels of education" (Kuh, 2013, p. v). Although the AAC&U values traditional measures of student success like persistence and graduation, it also recognizes the cumulative effects of participation in various college activities and the quality of the education provided. Through its focused leadership and dedication to improve student success rates, the AAC&U listed what was later to be recognized as high impact practice (HIP) activities, including

> [1] First year seminars and experiences, [2] common intellectual experiences, [3] learning communities, [4] writing-intensive courses, [5] collaborative assignments and projects, [6] undergraduate research, diversity/global learning, [7] Service Learning (SL), [8] community-based learning, [9] internships, and [10] capstone courses and projects. (Kuh et al., 2017, p. 10)

The resulting work articulated structures for "effective educational practices that, according to a growing array of research studies, are correlated with positive educational results for students from widely varying backgrounds" (Kuh, 2013, p. 1). These HIPs evolved from decades of seminal work on improving institutional success as measured by individual student persistence and institutional rates of retention (Astin, 1993; Bok, 2006; Bransford, 2000; Chickering & Gamson, 1987; Cross, 1999; Etkina, Mestre, & O'Donnell, 2005; P. M. King & Mayhew, 2002; P. M. King & Mayhew, 2004; Millis, 2016 Pascarella, 2006; Pascarella, Wolniak, Seifert, Cruce,

& Blaich, 2005; Ramaley & Haggett, 2005).

The research study documented here is intended to contribute to existing student success research that used data from the National Survey of Student Engagement (NSSE) and the Faculty Survey of Student Engagement (FSSE). The seminal research studies have demonstrated a positive correlation of HIP activity participation and the persistence for students (Brownell & Swaner, 2010). The studies begin to address differentiating effects of persistence on certain student subgroup populations. Various studies on student success using NSSE results reveal that underrepresented subgroups of student participants realize greater positive impacts of persistence from HIP activity participation. Kuh (2013) observed that, "engagement and persistence are positively correlated for all students…as the African American students become more engaged [in HIP activities], they also become more likely to surpass white students in likelihood they will persist" (Kuh, 2013, p.19).

Service Learning

Service learning (SL) has been categorized as 1 of the 10 HIPs (Kuh et al., 2017). At the end of the 20th century, society began to expect public land-grant institutions to adequately educate and prepare students for productive citizenship (Boyer, 1990). The emphasis required institutions to re-evaluate their structures to further enhance the student experience through broader scholarship-based teaching, research, and service (Ramaley, 2000). Responding to this call for change, the Kellogg Commission on the Future of State and Land Grant Universities (2000) challenged higher education to be more responsive and engaged with local communities through strategic and collaborative partnerships. As of 2015, 361 American institutions had elected to modify their practices to obtain a recognized classification of Carnegie Engagement (Saltmarsh & Driscoll, 2015). In 2018, Utah State University (USU) began the application process for this classification. A residual outcome for this study is to provide evidence to the

Carnegie Foundation that USU has the capacity to employ evaluation methods to estimate student success impacts of respective curricular and co-curricular engagement activities.

State and national higher education organizations, like The National Association of System Heads (Strategic Initiatives, 2018) and Utah's System of Higher Education (USHE) have positively acknowledged AAC&U's student success research outcomes and have mandated all Utah institutions of higher education to "establish the goal that all students participate in two HIPs during study at the undergraduate level: (1) one during their first 30 credits of enrollment (not including concurrent enrollment) and (2) one within their major" (Buhler, 2017).

This study employed research methods that measured the effects of a curricular HIP activity on student success. The study limited its scope of analysis to estimate the impacts of student participation in USU courses with the designation of SL. SL-designated courses were openly available to all students at USU and, depending on the course, contributed to either upper or lower division credits. In order for a course to receive a SL designation, its curriculum must align with the AAC&U's categorical definition for SL:

> In these programs, field-based "experiential learning" with community partners is an instructional strategy—and often a required part of the course. The idea is to give students direct experience with issues they are studying in the curriculum and with ongoing efforts to analyze and solve problems in the community. A key element in these programs is the opportunity students have to both apply what they are learning in real-world settings and reflect in a classroom setting on their service experiences. These programs model the idea that giving something back to the community is an important college outcome, and that working with community partners is good preparation for citizenship, work, and life. (Kuh, 2013, p. 11)

This study selected SL because USU's Center for Community Engaged Learning followed a structured process to determine whether courses satisfy the necessary curriculum requirements to receive a SL designation (see Appendix B). Although it is important to recognize that a primary outcome of a SL curriculum is to develop socially beneficial citizens (Kuh, 2013), it is also important to understand that "students who engage in community service, volunteering, and SL opportunities have positive outcomes related to retention" (Howe & Fosnacht, 2017, p.

160). As a result, Utah political and higher education leaders are recommending that students participate in curricular HIP activities like SL to not only develop good citizens but to persist on to graduation.

The statistical methods used for this study required large numbers of participants to obtain significant results. According to the 2013 NSSE, there more ethnically diverse participants in SL activities than any other categorized HIP (NSSE, 2013b). It should also be noted, even though it was only a relatively small difference, that greater numbers of non-White students participated in SL. USU is predominantly white, and one of the research questions for this study was to discover the impacts of participation on subgroup populations of students, which includes categories of ethnicity.

Sustained student success in higher education requires institutional leaders to properly use limited resources for activities and programs intended to improve rates of persistence and reduce graduation timelines. Consequently, educational leaders are challenged to determine what curricular and co-curricular programs affect student success outcomes—both positively and negatively. Using term-to-term persistence as an indicator of student success allows timely analysis that can be used to adjust curriculum programming. This study employed valid and reliable methods and tools designed to discover how SL activities contributed to or inhibited student success at USU.

Significance and Problem Statement

A principal imperative of university administrators charged with the management of institutional programs and activities is to simply know "what is going on" (Ewell & Jones, 1996, p. 1). These administrators are challenged to make informed decisions in an environment of constantly changing instructional methods and curricula. Amidst a constant barrage of innovative research-based programs, faculty and administrators alike are implementing new activities designed to positively affect student success. “Most colleges and universities are awash in data but thirsty for information that points to *how* to become more effective and efficient” (Kuh, Kinzie, Schuh, & Whitt, 2011, p. 15). In order to understand the current environment and solve the problem of decision making with limited information, educational leaders can use the research methods employed in this study to estimate the impacts of extant curricular or co-curricular activities on student success outcomes.

Alexander Astin (1970), one of the most prominently cited researchers in college student success, spoke of a need for institutions to measure their effectiveness during a time when comparisons between academic institutions were becoming more competitive. “With the greatly expanding higher educational opportunities and the extraordinary diversity among institutions, the question of impact of college increasingly is coming to be one of the comparative impacts of different types of college experiences” (p. 437). Fifty years later, public institutions of higher education differentiate themselves by innovative curriculum and delivery methods, but there still exists healthy competition for public funding. Consequently, it is an institutional challenge to measure the effectiveness of existing higher education experiences and to defend whether they produce the intended student success outcomes.

Social science research has examined student success in higher education for decades, and much is known about the generalizable positive effects on student outcomes from participating in HIPs (Kinzie & Kuh, 2017). Nevertheless, researchers have cautioned that not all colleges and universities are the same, nor are their incoming students (Chickering, 1972; Pike, Kuh, & Gonyea, 2003). Pascarella and Terenzini (2005) emphasized the importance of accounting for the differing student backgrounds when measuring the effects of institutionally implemented activities. Methods of evaluation must control for differences in students’ backgrounds, which is an inherent challenge when attempting to measure the impacts of institutionally supported activities.

Our academic and political leaders need assessment solutions that provide insights on the impacts that extant activities have on student outcomes. Consistent with prior research, positive impacts of persistence on students who participate in the high-impact practice of SL is anticipated when compared to their counterparts; however, prior research methods do not provide insights on the impact that locally designed activities have on their bodies of students.

Research Questions

This study examined the treatment impacts of persistence on students who participated in SL courses at Utah State University. The following three research questions were used to guide this study.

1. Does participation in the curricular high-impact practice of SL have a significantly positive difference in the means on students' likelihood to persist to the next term?
2. Is there a significant difference in the student persistence mean values based on SL course levels (e.g., lower division or upper division)?
3. Do the difference in student persistence mean scores vary based on subgroup populations of students who participate in the curricular high-impact practice of SL?

Conceptual Model

Alexander Astin was a trained psychologist who applied his behavioral research skills to higher education where he devoted his career to understanding the impacts colleges have on their students. After approximately 15 years of research, a theory of student involvement emerged from his work and can be explained with his simple statement, "Students learn by becoming involved" (Astin, 1985, p. 133). The theory of involvement is based on *cathexis*, a Greek term meaning retention and coined by Freud to explain unhealthy amounts of energy focused on a single object. Astin's theory claims the amount of time and energy students expend on college activities will influence their behavioral outcomes (Pascarella & Terenzini, 2005).

Pike, Kuh, and Gonyea (2003) structured their educational research methods using Astin's input, environment, and outputs (IEO) model to assess the impacts of student engagement, "or involvement in educationally purposeful activities, on student learning" (p. 244). By following the IEO model they accounted for student inputs that may have skewed research outcomes through self-selection bias, their methods held student input characteristics constant, and in accordance with the model, assumed the characteristics influenced student outputs. A body of student involvement research reported positive gains of learning on male, female, and other minority subgroups; however, first-generation students did not realize similarly positive outcomes to their counterparts (Astin, 1993; Chickering & Gamson, 1987; Pascarella & Terenzini, 2005).

Even though measured levels of student involvement in college activities demonstrated positive results, the researchers discussed future implications and recommended that, "Rather than trying to increase involvement, scholars and practitioners should seek to identify ways in which the integration of experiences can be improved. This will not be a simple task" (Pike et al., 2003, p. 258).

This study was guided by Astin's IEO model of student development in higher education. The conceptual IEO model has proven its effectiveness over time and is an adaptation of earlier versions that Astin (1965, 1970, 1999) developed to research higher education. Astin and Antonio (2012) have validated the use of the IEO model and described it as, "Simple, it provides a powerful framework for the design of assessment activities and for dealing with even the most complex and sophisticated issues in assessment and evaluation" (p. 17).

This study's methods were guided by Astin and Antonio's IEO model by employing a quasi-experimental research design to analyze observational student data. "The basic purpose of the IEO model is to allow us to measure relevant input characteristics of each student and then correct or adjust for the effects of these input differences in order to get a less biased estimate of the comparative effects of different environments on outputs" (Astin & Antonio, 2012, p. 21). It is comprised of three conceptually distinct components: student inputs, the environment, and student outputs (see Figure 1).

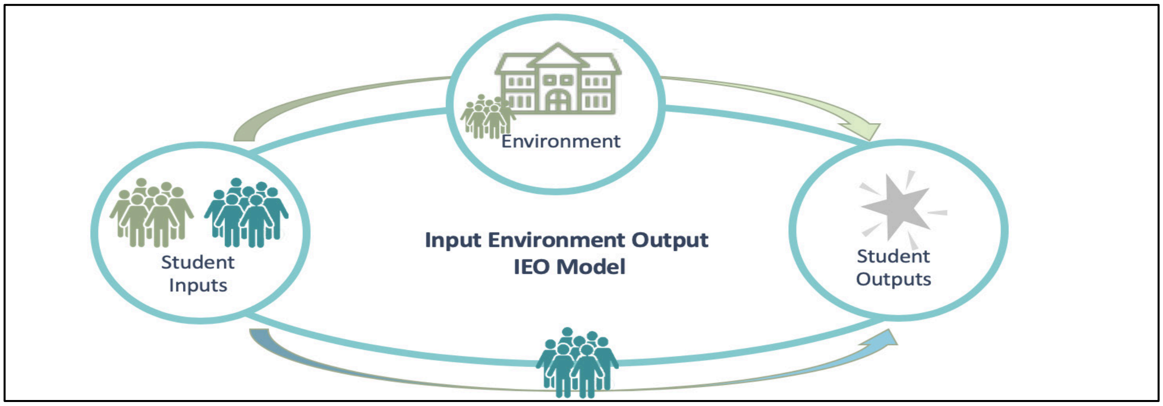

Figure 1. Input, environment, and output model.

Student inputs. Students bring inherent individual attributes with them to college. Static attributes such as gender, race, socioeconomic status, and so forth are essentially raw characteristics commonly used to categorize populations, whereas individual attributes such as GPA, standardized test scores, credits earned, etc., are academic indicators of student performance. Student inputs can affect student outputs either directly or by association with environmental variables. Methods employed for this study leveraged available student input covariates to derive predictor variables (Harder, Stuart, & Anthony, 2010; Kil, Derr, et al., 2017) used to match individuals from groups of participant and control students.

The environment. The environment refers to aspects of higher education capable of affecting student outputs. "Broadly speaking, they include administrative policies and practices, curriculum, physical plant and facilities, teaching practices, peer associations, and other characteristics of the college environment" (Astin, 1970, p. 225). This study used a more granular definition of the environment: an intentionally designed institutional activity expected to produce positive student outcomes. The HIP activity of SL, administrated by USU's Center for Community Engagement, is a structured curricular program intended to produce positive student success-related outcomes of persistence (Howe & Fosnacht, 2017; Kuh, 2013). Methods employed in this study isolated the environment (activity) from confounding student input variables to determine its effects on participating students when compared to control (non-participating) students.

Student outputs. Student outputs are aspects of a student's behavior that the institution either influences or attempts to influence (Astin, 1970; Astin & Antonio, 2012). Student success research has been concerned with outputs that can be operationalized, such as attendance, skills acquisition, academic achievement, persistence, etc. Results from this study compared the behavioral outcome measures of persistence between participant and control groups of students, and the employed methods estimated impacts on students who were exposed to the intentionally designed activity within the educational environment.

The conceptual IEO model was used to guide the research methods employed in this study to estimate the impacts on persistence of the curricular high impact practice of SL. The methods used individual student characteristics to eliminate outcomes error from self-selection bias. The characteristics were also used to isolate the SL activity as the only differentiating variable between the two analyzed groups of students.

Operational Definitions

Bootstrap resampling: An iterative resampling process that randomly selects individuals from a control group and attempts to match them with statistically similar individuals in a participant group. Resampling iterations using a restricted caliper width is used to account for possible covariate imbalance (Rubin, 1976, 2008). Methods employed in this study require that each student must be included in one or more bootstrap iterations–otherwise they are thrown out of the analyzed population.

Counterfactual: An estimated result of what would have happened in the absence of a treatment.

Difference in difference: A popular estimator technique that uses observational and non-experimental data to mimic experimental research design to interpret differences in effect size measures (Abadie, 2005). Using the statistical difference in difference technique, this study will compare the calculated means from the bootstrapped iteration distributions of the predicted persistence rates and the actual persistence rates of the participant and control groups of students.

Environment: An intentionally designed activity expected to produce positive student success outcomes (Astin & Antonio, 2012).

Extant activities: Activities designed to support a programmatic mission of an institution and not for the primary purpose of research, and where historical and observational data about currently active or prior participants is available for assessment.

High-impact practices (HIPs): Intentionally designed teaching and learning experiences that have proven beneficial results for college students with various backgrounds. "First year seminars and experiences, common intellectual experience, learning communities, writing-intensive courses, collaborative assignments and projects, undergraduate research, diversity/global learning, SL, community-based learning, internships, and capstone courses and projects" (Kuh et al., 2017, p. 10).

Learning analytics: Is the organization and analysis of data associated with student learning used to understand behaviors and design appropriate interventions (Brown, 2011).

Leave of absence (LOA): Students who intentionally stop attendance for a variety of reasons, such as military or religious service. The predictive models used in this study to derive scores of persistence have been calibrated to account for the institution's unique LOA populations.

Machine learning: A computationally demanding approach to mine unstructured data by finding regularities and patterns or extracting meaningful semantic information (Bienkowski, Feng, & Means, 2012).

Prediction based propensity score matching (PPSM): A statistical technique that extends traditional propensity score matching to eliminate self-selection bias by applying machine learning analytics to incorporate a large number of covariates into analyses (Kil, Derr, et al., 2017).

Propensity score matching (PSM): A statistical technique that uses observed and individual student input covariates, PSM matches analyzed groups of students based on their relative common probability scores to participate in a treatment. PSM is a commonly accepted method used to eliminate confounding bias when using observational data by matching statistically similar individuals analyzed in a study (Rosenbaum & Rubin, 1983, 1985; Rubin, 1976, 2008; Rubin & Thomas, 2000).

Persistence: Continued term-to-term enrollment for university students. Persistence is a significant outcome, as it is an indicator of a student's progress towards graduation (Kuh, 2013).

Retention: An institutional metric of student behavior illustrating rates of students staying in school from one term to another.

Subgroups: Categorical features or unique characteristics of student groups.

Delimitations

This study employed statistical methods intended to reduce bias found in large secondary and observational data sets from participants. The employed methods did not use student input factors to account for outcomes, instead, they were used to statistically match comparison groups.

The analyzed covariates used in this study were limited to the following characteristics: academic performance, degree progression metrics, socioeconomic status, and online course engagement metrics (Kil, Derr, et al., 2017). What was not considered in this study or accounted for were detailed measures of a student's holistic environment and psychological aspects that contributed to persistence outcomes. Given the available data sets and employed methods, latent constructs such as an individual's motivation were neither assessed nor included in this study and limited the extent to which this research can explore contextual effects that may influence a student's likelihood to persist. The available data used for this study did not include affective traits of analyzed students and faculty members that teach SL courses. Analyzing affective domains for students or faculty were out of this study's scope and were not necessary to answer the proposed research questions.

Summary

The history of higher education illustrates an unceasing demand for institutions to adapt to continually evolving societal needs. In addition,

> …to create serious change at a research university [it] requires change in the culture and understanding of research…. It speaks to the need to embed change priorities in core reporting, budgetary and accountability structures of the university. (Fitzgerald, Bruns, Sonka, Furco, & Swanson, 2016, p. 227)

Student persistence is a consequential behavior influenced by a culmination of individual characteristics and experiences that may be unique to an institution and its student population (S. A. Becker et al., 2017). Past student success research provides generalized evidence that supports organizational, curricular, and co-curricular practices designed to improve rates of student persistence and ultimately reduce graduation timelines. By recognizing the complexities involved in understanding influential student and environmental factors determining student retention, the Hanover Research Council (2010) recommended institutions develop their own learning analytic systems to understand their unique student behaviors. “With such knowledge, institutions will be better able to identify students particularly at-risk of dropping out, as well as develop programs and practices that can address the issues influencing their decision to stay or leave” (p. 2).

The purpose of this study was to estimate impacts of student participation in the curricular HIP of SL. This study intended to contribute to the research literature by discovering the difference in persistence outcomes between individuals and subgroups of participating and non-participating students. By using robust learning analytic tools, this study also intended to provide academic leaders with techniques to assess HIP activities in a timely manner. It also intended to contribute valid and reliable methods used to understand whether university activities contribute to or inhibit student success in higher education.

Chapter I provides background information on the role of higher education, measures of student success, and a conceptual model used to guide this study. Chapter II will provide an overview of theories that contribute to student success in the context of higher education. A brief review of prominent research literature will be organized by student input characteristics and institutional environmental factors that influence student success outcomes. Furthermore, it will conclude with a review of documented research using similar statistical methods proposed for this study. Chapter III will provide a methodological blueprint that employs a quasi-experimental design using observational and nonexperimental data to estimate treatment effects on student persistence. Chapter IV explains significant analytic results of the research questions in Chapter III organized by research question and corresponding hypothesis. Chapter V is a discussion of the insights derived from the analyzed results found in Chapter IV. It will include a comprehensive analysis of each research question and provide explanations of what the results may mean along with future implications.

CHAPTER II

LITERATURE REVIEW

A vital imperative for academic leaders in higher education is to develop quality curricular and co-curricular programming. As public funding has been increasingly limited, accreditors and politicians have placed greater accountability on institutional decision making (Van Campen, Sowers, & Strother, 2013). This has presented a challenge to institutional leaders and faculty members to measure and demonstrate activity effectiveness. Meaningful assessment of academic programming requires an understanding of what conditions should produce positive student outcomes and what methods of analysis will yield actionable data (Kuh et al., 2015; McCormick, Gonyea, & Kinzie, 2013).

Even though American colleges have existed since 1636 when John Harvard seeded the first college, research to understand student success as measured by persistence and graduation has only been conducted in the last 50 years (Berger & Lyon, 2005; Carey, 2016). The early colleges were hard pressed to stay open long enough to celebrate graduations for their initial student cohorts, and, throughout the 1900s, there grew an emphasis to provide insights on what notable input characteristics influence student success outcomes, irrespective of institutional environmental treatments.

Methodology for this research study, described in Chapter III, was designed to account for a wide variety of student inputs that may have contributed to or confounded the analysis of the treatment outcomes. The selected methods were used to account for large numbers of student inputs that were held constant to statistically compare outcome behaviors between the two groups of analyzed students. The following review of selected literature was organized using Astin and Antonio’s (2012) inputs, environment, and outputs (IEO) model to complement the research methodology. This chapter will provide an overview of a multitude of influential factors that are included in various models and theories on why students succeed in college. The organization used to describe the selected literature was not intended to be linear, but, rather, it was organized to help the reader compartmentalize how the models or theories explain the expected outcomes of characteristics students bring with them (inputs) to college, or the environmental (environment) influences and their impacts on student success (outputs). The organization of this review of literature will incrementally narrow its focus from institutional/university-level structures down to activity-level treatments, and what their impacts have been on participating students. Finally, the student outputs section will present existing research literature that supports using the statistical methods proposed for this study. To narrow the selection of student success models and theories, they must explain phenomena that impact and are closely aligned with criterion outcomes for student persistence, retention, and degree completion. The selected research presented in this chapter intends to illustrate relationships that support the IEO conceptual model and will be referenced in Chapter V when discussing the discoveries of the research results presented in Chapter IV (Figure 2).

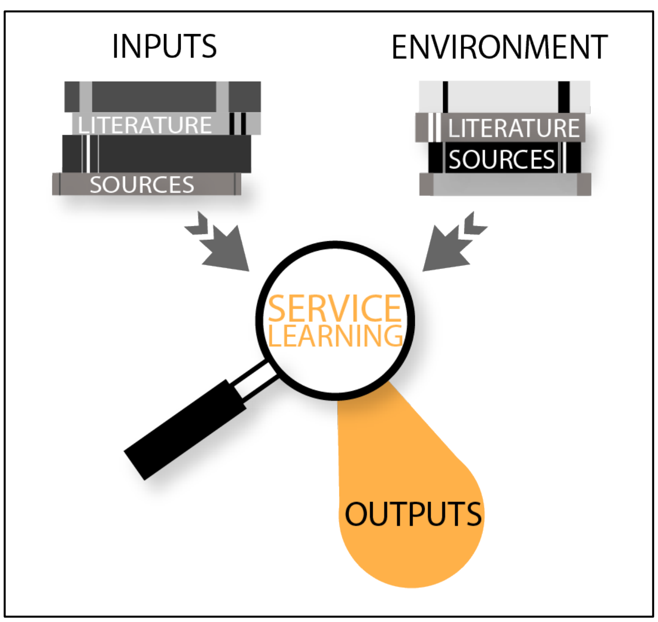

Figure 2. Literature organization by the IEO model.

Student Input Factors

This student input factors section is a selection of literature that includes descriptions of various theories of student success and applicable models selected to explain the differing effects that individual student characteristics have on outcomes. “It is difficult, if not impossible, to learn how our educational policies and practices affect student outcomes in the absence of input data on the entering student” (Astin & Antonio, 2012, p. 69).

Research has illustrated how individualistic characteristics such as demographics, academic performances, family and community support, etc. directly influence student persistence and degree completion (Astin & Oseguera, 2012; DeAngelo, Franke, Hurtado, Pryor, & Tran, 2011). In addition, complementary studies of single and multiple institutions have demonstrated similar effects for various levels of economic status and ethnic groups of students (Astin, 1982; Huerta & Fishman, 2014). The collective term for these characteristics is Student Input Factors (see Figure 3). The body of student success research literature does not provide a common taxonomy for student input or academic environmental characteristics; however, after reviewing the literature, two descriptive categories emerged: definite or variable. Definite student attributes include race or ethnicity; whereas variable student attributes can change over time and may also include measures of demographics, cognitive abilities, values, goals, attitudes, behaviors, and educational backgrounds. The following review of literature is organized by the IEO model, and not categorized by the definite or variable student attributes. Nevertheless, this taxonomy can be used to further describe respective student characteristics in future research studies.

Gender is a definite and fixed student attribute that students bring with them to college. It is a useful characteristic to categorically separate analyzed students where outcome insights can influence designs of curriculum and instruction. When holding gender constant, research results

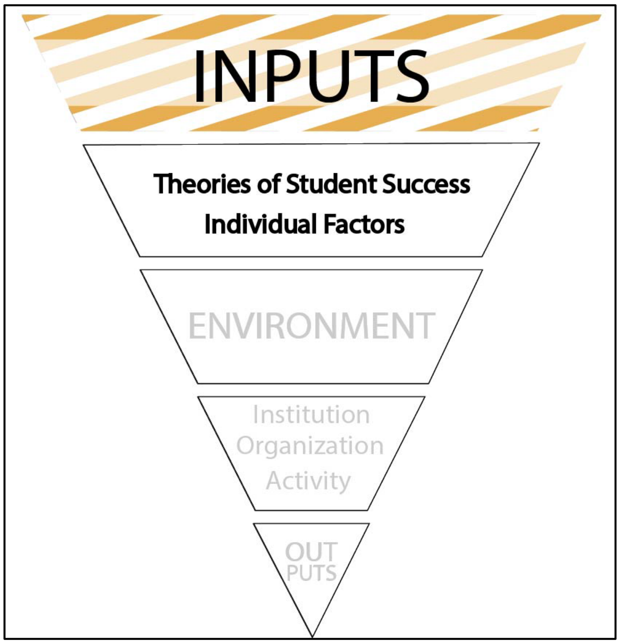

Figure 3. Student input factors.

have been mixed on rates of retention and degree completion. Longitudinal studies by Tinto (2012) discovered gender is a significant factor related to the outcomes. They were also able to demonstrate that females were more likely to be retained when compared to their male counterparts (Milem & Berger, 1997). DeAngelo et al. (2011), studied 4-, 5-, and 6-year degree completions outcomes and found similar results. However, other prominent researchers like Pascarella and Terenzini (2005) found impacts were related less to gender and rather emphasized the influential effects of student interaction on rates of retention and graduation. Interestingly, Titus (2006) examined 6-year graduation rates for student groups categorized as low economic status and did not find significant differences by gender.

Additional research on variable student attributes has demonstrated that student persistence and degree completion has varied based on individual characteristics of demographics, academic performances, and financial status (Astin & Oseguera, 2012). Prior methods of analysis in studies have suggested to hold potentially influential input factors constant when analyzing student outcomes (Garrido et al., 2014; Giani, Alexander, & Reyes, 2014). By so doing, the activity introduced to students in the university environment becomes the differentiating variable and student success outcomes can be measured.

Astin's (1975) early assessment work on higher education revealed two categorical factors that can be used to predict student success outcomes: individual student characteristics and the institutional environment. The respective factors described in each category are still used today for predictive modeling and research methodologies (Kil, Chan, Wimalasurya, & Gee, 2017; King & Nielsen, 2016; Nosaka & Novak, 2014). The following individual factors, listed in a descending order of influence, were identified by Astin (1975) as predictors for student persistence in college:

1. Past academic grades–those with stronger past academic grades were more likely to persist.
2. Educational aspiration–those with higher degree aspiration were more likely to persist.
3. Study habits–those who turned in homework on time and did homework at the same time every day were more likely to persist.
4. Parents' education–those with more educated parents were more likely to persist.
5. Marital status–married males and single females were more likely to persist. (Seidman, 2012, p. 67)

Astin's (1985) assessment work continued to leverage the IEO model where he applied greater fidelity to understand the impacts of the educational environment. His early discoveries have since been supported by Pascarella and Terenzini (2005). Other sociological research during the 20 years between 1970 and 1990 produced a flurry of discoveries that help us understand why students stay in and drop out of college (Meyer, 1970, Ramist, 1981; Spady, 1970; Tinto, 1975, 1993). More recently, Chambliss and Takacs (2014) found correlations between student involvement in the college environment and student outcomes. The research found that "the amount of student learning and personal development associated with any educational program was directly proportional to the quality and quantity of student involvement in the program"

(Astin, 1985, p. 136).

Future studies acknowledged the value of Astin's categories and have been used to structure the collection and organization of longitudinal data sets. In 2010, the National Center for Educational Statistics (NCES) published a study on post-secondary student persistence and degree attainment outcomes. The study, sponsored by the Department of Education, provided a longitudinal dataset reporting rates of certificate and degree completion of differing students and backgrounds (Radford et al., 2010). The NCES data and its study entails both student and institutional information that includes historical enrollments, transfers, and completions.

Statewide systems of educational institutions are particularly interested in data similar to NCES that tracks students who leave one school and transfer to another. A system values persistence within its institutions as a measure of student success, especially when students transfer, persist, and graduate within their system (Fuller, 2012; Roberts & Styron, 2010). The state of Utah reported on a student transferring phenomenon where, "1 in 5 Utah System of Higher Education (USHE) students enrolls and completes at the same institution, in the same major, and at the originally-intended award level" (Curtin, 2017, p. 1). The report continues to explain that movement across this system may be of concern to individual institutions; however, transferring between institutions "is both a positive and intentional outcome that is a cost-effective, flexible opportunity for students" (Curtin, 2017, p. 4).

Student retention in higher education is a high-stakes activity for institutions, families, and students. The financial relationships between students and institutions are complex and have severe implications for institutions when students fail to persist to graduation (Bok, 2006). According to Levitz (2009), the associated institutional costs to recruit a student to a 4-year public college was $461. If that recruited student persists to graduation within 4 years, the cost per student is reduced to less than $120 per year. Once a student drops out, an institution must reinvest another $461 in hopes of recruiting a persisting student, and it never recoups the initial investment.

In 2008-2009, American institutions spent more than $263 billion on education-related expenses. During those years, 35% of the 2003-04 cohort of undergraduates failed to graduate (N. Johnson, 2012). This was categorized as a tremendous loss. More recently, local attrition rates similar to historical national rates are plaguing schools like USU in 2018 where only 72.6% of first-year undergraduates were retained from 2017-2018. Student attrition from higher education comes at a high expense. The negative financial impacts of nonpersisting students are complex and adversely affect immediate direct, indirect, and long-term costs to the institution and individual students (Schuh & Gansemer-Topf, 2005). The nonpersisting and nongraduating students result in a cost multiplier of a lifetime of lower income potential, lost tax revenues for local communities, and a higher likelihood of defaulting on educational debts (Seidman, 2012).

Tinto's (2012) Longitudinal Model of Departure, discussed later in this chapter, illustrates individual characteristics that may contribute to student persistence at a single institution. However, the model does not account for persistence to other post-secondary institutions. It may seem limiting from the perspective of a statewide system to not account for students who "swirl" (Curtin, 2017) from one institution to the next, but reducing the scope when tracking student persistence is necessary to attempt to understand what factors contribute to retention and degree completion. Research literature on student persistence reviewed for this study will be limited in its scope to include only models and theories explaining student behaviors at an individual institution and will not account for student behaviors once they leave.

Theory of Involvement

When discussing issues of student persistence in higher education, there are two prominent theories that emerge in the literature: the theory of involvement (Astin, 1984) and the theory of student departure (Tinto, 1975, 1993). Pascarella and Terenzini (2005) recognized the two theories to be “among the most widely cited approaches in the higher education literature” (Milem & Berger, 1997, p. 387).

Astin (1999) developed the theory of involvement to organize his 20 years of higher education research to “bring some order into the chaos of literature” (p. 518). He also developed the theory to use as a guide for researchers and administrators. The involvement theory explains how much a student contributes in time and resources to an academic experience. It argues that to achieve desired educational outcomes, educators must “elicit sufficient student effort and investment of energy” (Astin, 1999, p. 522).

The term involvement was very much intended to be a behavior construct. “It is not so much what the individual thinks or feels, but what the individual does, how he or she behaves, that defines and identifies as involvement” (Astin, 1999, p. 519). There are five precepts that guide the theory:

1. Involvement requires the investment of psychological and physical energy in “objects” (for example, tasks, people, activities) whether specific or highly general;
2. involvement is a continuous concept where different students will invest varying amounts energy in different objects;
3. involvement has both quantitative and qualitative features;
4. the amount of learning or development is directly proportional to the quality and quantity of involvement; and
5. educational effectiveness of any policy or practice relates to its capacity to induce student involvement. (Pascarella & Terenzini, 2005, p. 50)

Astin asserted the value of educational experiences, with regards to student persistence, are directly correlated with levels of involvement, and his theory bridges the psychological and sociological reasons for student success. As a psychologist, Astin’s (1965, 1970) work, placed emphasis on student input factors that influenced the outcomes. However, the theory of involvement accounts for a variety of environmental factors that students may experience at an institution and, more importantly, how the behavioral involvement influences their outcomes.

Milem and Berger (1997) conducted a study to investigate the relationships and differences between Astin's theory of involvement and Tinto's interactionalist model of student departure. Using words similar to Tinto, they stated, "the more students learn, the more they are likely to persist" (Milem & Berger, 1997, p. 388). Their findings concluded that positive impacts on persistence result from student involvement, which influences student perceptions of support from their institution and peers. An earlier comparative study of the theories by Hossler (1984) also found that students' precollege characteristics and interactions affect how well students adjust to their institution and persist on to graduation (Cabrera, Castaneda, Nora, & Hengstler, 1992). To summarize the previous 20 years of undergraduate research on student involvement, the most positive and influential forms of involvement are with academic advisors, faculty, and student peers; not being involved has conversely negative impacts on degree completion (Seidman, 2012).

Theory of Student Departure

There are a number of student success models based on seminal work by Vincent Tinto designed to explain why students persist and how to retain them (Pascarella & Terenzini, 2005; Seidman, 2012, 2018). Institutional decision making focused on student success requires a holistic view of the student life cycle to make actionable decisions. Tinto's (1993) Longitudinal Model of Student Departure provides a framework that strategically guides the development of activities and resources intended to help students persist to graduation. The model of student departure was designed to follow a chronological path, beginning with a student's admission and ending at the completion of their personal and institutional goal and commitments. The model structure accounts for attrition from the institution at any point of the student life cycle; however, it does not account for students once they have left the institution, nor does it provide insights into whether students transfer to another school or drop out of college altogether.

Students enter an institution with a wide variety of individual input characteristics like family backgrounds (sex, race, social economic status, parental education, community, etc.), skills and abilities, and prior academic performance (high school GPA, transfer credits, etc.). According to this model, each of the prior attributes influence a student's disposition to reach their educational goals and commitments. According to Tinto (1993, 2012), there is a compounding effect on whether students stay or depart from college based on their pre-entry attributes, student disposition, and interactions with fellow students, staff, and faculty. Various research findings have provided evidence that interpersonal interactions through curricular or co-curricular university activities make a difference whether students choose to stay or depart (Brownell & Swaner, 2010; Manning, Kinzie, & Schuh, 2013). In other words, student engagements matter, and they foster the development of valuable relationships that have shown to increase a student's likelihood to persist on to graduation (Chambliss & Takacs, 2014).

As explained in Tinto's (2012) model, positive academic and social integrations directly influence goal commitments and intentions to complete a degree at a registered institution. Conversely, the less a student participates in academic and social communities, the greater the likelihood that a student will depart from the institution. Students are influenced by external forces including, but not limited to, family, work, and local communities. According to Tinto (1993, 2012), these have impacts on student persistence or departure throughout a student's life cycle. When external communities are strong, a typical scenario for nontraditional students enrolled in rurally located campuses, they have a greater influence on a student's choice to stay enrolled (Bean & Vesper, 1992).

Once students complete the admissions process, an institution is responsible for supporting their potential success through graduation (Tinto, 2012). This presents a challenge to publicly funded 4-year universities in which 29% of students are accepted through open enrollment policies (Kena et al., 2016). As a result of an increased dependence on tuition dollars, institutions are compelled to openly enroll students and face greater risk of accepting underprepared students. As early as 1992, 97% of high school graduates planned to continue on to post-secondary education. Of those, 71% expressed interest in obtaining a bachelor's degree (Choy, 1999). With a growing interest from demographically diverse students, institutions must consider programming designed to positively influence persistence for under-represented groups (Kena et al., 2016).

Although there is a wealth of research regarding why students leave college, "most [studies] have been neither very effective in explaining departure nor particularly well suited to the needs of institutional officials who seek to retain more students on campus" (Tinto, 2012, p. 84). As higher education researchers seek to advance the next generation of scholarship on student success and retention, attention to malleable processes within students and the differential effects of such processes on student success offers opportunities for new insights into the ill-structured problem of student departure (Schreiner, Pothoven, Nelson, & McIntosh, 2009, p. 2).

The longitudinal theory of departure provides a conceptual framework for research explaining why students leave and what may be necessary to help them persist to graduation. Initial research in this area focused on psychological models attributing the importance of intellectual abilities to meet the demands of higher education (Marks, 1967; Summerskill, 1962). Other researchers stressed the roles of personality, motivation, and an individual's disposition as significant influential factors contributing to departure from college Kuh, Kinzie, Schuh, and Whitt (2011) pointed out that although psychological research is to be considered, it is insufficient to holistically explain why students are leaving because it typically accounted for student behavioral responses in similar educational circumstances.

Student Adjustment Model

Developed from the theory of involvement (Astin, 1984) the student adjustment model

(Nora & Cabrera, 1996) and the longitudinal theory of student departure (Tinto, 1975, 1993), were established as structures to guide educational leaders when designing curriculum and instruction that positively influences student persistence to graduation. It argues that student persistence behaviors result from an interconnected set of experiences between students and their academic environments. Like Tinto (1993), Nora and Cabrera differentiated student experiences by domains of social interactions, such as with peers, institutional faculty, and staff, that collectively increase institutional commitment leading to degree completion.

Like Tinto (1975, 1993) and Astin (1984), the student adjustment model accounts for influential precollege student inputs directly influencing persistence for minority and nontraditional students. The model demonstrates the amount of student academic preparedness has no significant difference on comparative groups of minority and nonminority students. Similarly, academic performance was no different between ethnic subgroups of students with similar precollege academic backgrounds (Nora & Cabrera, 1996).

Student/Institution Engagement Model

Nora, Barlow, and Crisp (2006) proposed a student/institution engagement model that emphasized student interactions with the academic environment (Nora, Barlow, & Crisp, 2006). This model builds on Tinto's (1993) work and demonstrates the cumulative effects of student input factors, college experiences, and community influence on persistence. Student input factors with the greatest influence on persistence are "High school experiences, academic achievement, financial circumstances, and specific psychosocial factors that are developed in both home and school environment" (Arbona & Nora, 2007, p. 250). The model also considers impacts of environmental influences such as responsibilities to family, work and community, and the distance students commute to and from school. Nora et al. were guided by the student/institution engagement model concluded that precollege characteristics and college experience data can effectively predict 4-year degree completion for minority students.

Human Capital Theory

Financial resources were not specifically specified in Tinto's (2012) longitudinal model of departure introduced earlier in this chapter; however, finances are part of a broader set of individual attributes, and the impact that financial resources have on persistence is viewed as indirect and are not accounted for. Nevertheless, there is a wealth of financial-related research on how socio-economic pressures will influence a students' disposition, intentions, and educational goals and commitments (Cabrera et al., 1992; Cabrera, Stampen, & Hansen, 1990). "Consumerism colors virtually all aspects of the college experience, with many colleges and universities 'marketizing' their admissions approach to recruit the right 'customers'—those who are best prepared for college and can pay their way" (Kuh et al., 2006, p. 2). Students already challenged with college preparation are working to avoid educational debt and consequently taking fewer credits per term, which is a predictor of college attrition.

Drawn from the field of labor economics, human capital theory seeks to explain the effects of financial and nonfinancial factors that influence students to persist in higher education (Paulsen, 2001). "Human capital is defined as the sum of productive capacities possessed by an individual or society, which encompasses knowledge talents, skills and understandings" (Franke, 2012, p. 19). The basic assumption of human capital theory, respective to higher education, is that individuals make educational investments to increase their capacity to obtain favorable economic returns. To decide whether to enroll in college, stay in college, or enter the workforce to improve their potential for productivity, families and individuals must continually weigh what often seems to be economically driven opportunity costs. According to G. S. Becker (1962), their human capital results in higher productivity whether their training investment is realized in higher education or from workforce experiences.

The theory assumes that people's choices are rationally based and well-informed. Paulsen (2001) reiterates that the primary opportunity costs on which individuals base their decisions on whether to attend college are either direct expenses or foregone earnings. Tuition, books, and cost of living make up direct expenses, whereas indirect costs are foregone earnings that students were not able to make while attending school.

The human capital theory model acknowledges that individuals are unable to accurately predict the value of obtaining degrees from higher education. It also accounts for individual investment decision making favoring immediate gratification and a combination of present and future benefits (Ehrenberg & Smith, 2016). The model reconciles gratification by positively weighting present values and discounting future benefits. It also assumes that all socioeconomic subgroups have equal access to higher education (Goldrick-Rab, Harris, & Trostel, 2009). This gross assumption means that incentives for going to college are equal for all student groups.

Despite its limitations, human capital theory confirms that reducing financial costs to students positively influences their likelihood to attend or persist on to graduation. The human capital theory provides financial decision-making insights that contribute to research in persistence and degree completion.

Full- and Part-time Enrollment

Part-time enrollment in higher education provides students flexibility, lower immediate costs, and greater access; however, part-time enrollment does not necessarily promote success for students. According to the National Center for Education Statistics in 2006, 37% of undergraduate degree-seeking students were categorized as part-time. Common behavioral characteristics indicative of leaving college for this group of students are excessive hours of work per week and poor continuity of term-to-term persistence (Berkner, He, Mason, & Wheeless, 2007; O'Toole, Stratton, & Wetzel, 2003). Individual characteristics associated with this group of students includes older and non-traditional, female, Hispanic, married, working full time, financially independent, first-generation, and they identify themselves as an employee rather than a student (Chen, 2007). Astin and Oseguera (2012) investigated the impacts of employment on students and discovered that working full-time is negatively related with student success outcomes; whereas, full-time students working part-time did not negatively impact on student persistence.

Sociological Reproduction Theory

Sociological theories are commonly cited in the research to explain student persistence and attrition. These theories attribute student decision making to social aspects of the individual, institution, and their surroundings. Social reproduction theory is almost always referenced in the respective research and has been extensively used to explain educational attainment.

In Bourdieu's economy of social practice, he recommended that social groups are to be strategically engaged to benefit current and future generations. Bourdieu (1974) emphasized it is important to integrate social networks to establish greater capital and use it as a strategic instrument for reform. "The school has become the most important agency for the reproduction of almost all social classes" (Nash, 1990, p. 432). However, the juxtaposition of human capital theory and social reproduction theory are to be considered if pursuit of social advantage is an intended outcome of public education. Human capital theory posits the role of education is to provide society with certified and skilled graduates (workers) who deserve to benefit in social roles (Bowles & Gintis, 1975; Labaree, 1997; Sweetland, 1996). Whereas, social reproduction theory assumes that education perpetuates social inequality and broadens the gap that give an advantage to students who are already in superior social positions (Aschaffenburg & Maas, 1997; Hirsch, 1978; Morrow & Torres, 1995).

First-Generation Students

A first-generation student has a unique and defining individual characteristic that she/he is the first member of their immediate and extended family to attend college (Pascarella, Pierson, Wolniak, & Terenzini, 2004). Consequently, many of these students do not have examples to follow or experienced family members providing guidance on what to expect from their college experience (Kenny & Stryker, 1996). In addition, many first-generation students made their college selection based on its proximity (less than 50 miles) to their home and intend on working 20 or more hours per week (Eagan et al., 2017).

As colleges and universities continue to focus on access initiatives and improve distance education options for place-bound students in rural locations, there will be growing numbers of under-prepared students. According to the Cooperative Institutional Research Program (CIRP) 2017 study, first-generation students are a large proportion of higher education enrollments and have high rates of attrition (Seidman, 2018). Table 1 compares the 1- and 2-year retention rate of full-time students at USU and throughout the nation and shows first-generation students are approximately 10 percentage points lower than their non-first-generation counterparts. Table 1 also shows that first-generation students are far less likely to graduate than students with degree-holding parents.

Environment and Educational Activities

The environment and educational activities section reviews selected literature that investigated the academic environmental effects on student success. Assessing aspects of the educational environment (Figure 4) that positively influence student outcomes has proven to be the most complex and difficult field of assessment (Astin & Antonio, 2012). When controlling for student input characteristics, Astin and Oseguera (2012) discovered the institutional environment

Table 1

One- and Two-Year Retention Rates and the Graduation Rate of First-Generation Students Compared with Non-First-Generation Students

		Retention rate		
Full-time students	Source	1 year (%)	2 year (%)	Graduation rate (%)
First-generation	USU	62.0	51.0	NA
	National	62.7	NA	11.0
Non-first generation	National	72.0	60.0	50.0

Note. Data for USU students from The Office of Analysis, Accreditation, and Assessment at USU (2018), for national retention rates from National Student Clearinghouse (2017), and graduation rates from Pascarella and Terrenzini (2005).

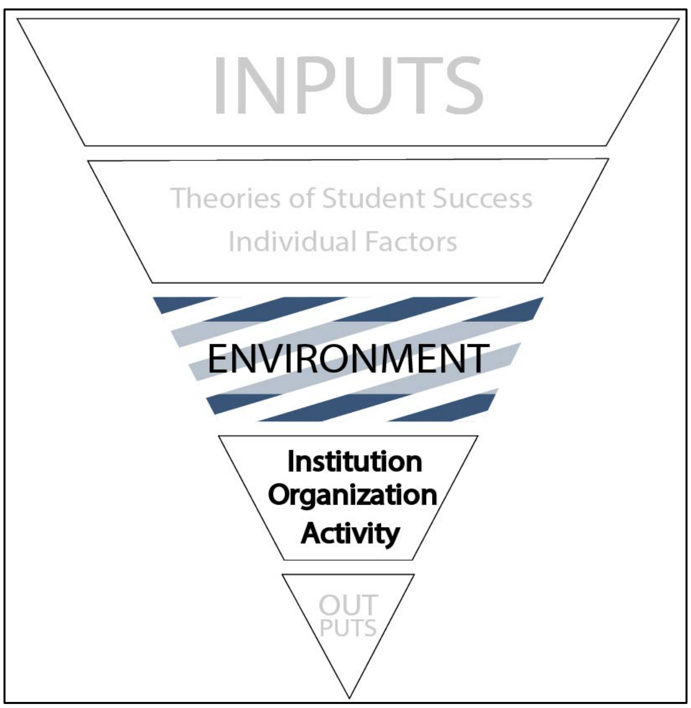

Figure 4. Environment.

influences student success outcomes, both positive and negative. Cope and Hannah (1975) explained there is not an individual that is “departure-prone.” More recently, Chambliss and Takacs (2014) explained that student success behaviors are as much a function of the environment as the personality traits that each individual brings to college.

Using the longitudinal model of departure as a guide, administrators can understand how to strategically implement system-wide student success initiatives and activities to produce positive outcomes. Successful implementation of actionable principles found in AAC&U's High Impact Practices (HIPs) and Tinto's model for departure requires acknowledgement that,

> Just as there is no single cause of a student leaving, there is no single program to successfully retain students. Successful retention programs are invariably the result of wide-ranging actions of diverse faculty and staff charged with responding to the needs of students in the diverse settings in which they interact. (Tinto, 2012, p. 151)

Like individual students, the educational environment varies from one institution to another based on its leadership and organizational structures. The following review of literature will begin with a broad view of the educational environment by investigating organizational and leadership theories and how they can influence student success. This section will then narrow its focus on intentionally designed activities that demonstrate positive student outcomes. This study measured the impacts of student success activities, using methods that isolated the activities (environment) as the only differentiating variable between analyzed groups of students.

Institutional Leadership

Leaders of educational reform have attempted to systematically improve institutional effectiveness by applying leadership and change management theories. Leadership theory is an interdisciplinary area of research and found in literature across disciplines including management, psychology, sociology, political science, public administration, and education. Prominently cited authors in topics of leadership, organizational change, system-wide reform, capacity building, and educational leadership are: Bass (1999, 2010), Bradford and Cohen (1984), Cohen and March (1986), Jago (1982), Kotter (1996), and Yukl (1989).

Vincent Tinto spent his academic career attempting to holistically understand student success initiatives. Tinto (2012) published notable institutional-level research that provided seven principles of action intended to structure implementation of student success initiatives intended for retention.

1. Institutions should provide resources and incentives for faculty and staff participation;
2. institutions should commit themselves to a long-term process of program development;
3. ownership of institutional change is to be in the hands of those tasked to implement it;
4. actions should be coordinated in a collaborative fashion to ensure systematic and campus-wide consistency;
5. faculty and staff must possess the necessary skills to assist students with retention efforts;
6. institutions should front-load retention efforts on first-year students, and
7. institutions and programs should continually assess their actions for continual improvement. (Tinto, 2012, pp. 149-152)

These premises illustrate a framework that emphasizes communication that contributes consistency across the system and continual improvement through evaluation strategies. Building on work by Deci and Ryan (1971, 1985), Tinto (2012) recognized the value of motivation as a foundational premise; this premise may be used as a strategic incentive by addressing human needs and motivate the participation of stakeholders. Lastly, Tinto recommended that student success initiatives must include mechanisms designed to continually assess their effectiveness to facilitate ongoing efforts of improvements.

Organizational Theory

Educational institutions are a culmination of various organizations with designs to influence behaviors of individuals and groups therein. The premise of classical organization theorists such as Luther Gulick and Max Weber used scientific management focused on the (1) management of work and the workers and (2) organizational structures (Shafritz, Ott, & Jang, 2015). Organizational theory studies the relationships, structures, external environments, and behavioral impacts on participants and organizational effectiveness. In the field of higher education, applications of organizational leadership tend to emphasize effects of academic leadership and governance (Berger & Milem, 2000). However, according to Oseguera and Rhee (2009), the field of study has overlooked impacts of the college environment on student outcomes.

"Undergraduate education is not merely a byproduct of other institutional operations (such as governance) but is, or at least should be, at the heart of institutional activity" (Berger & Milem, 2000, p. 178). Using organizational theory as a framework provides researchers the ability to investigate college and university environmental effects on student success outcomes (Shafritz et al., 2015). Over the years, organizational models evolved to recognize impacts of a multi-faceted and holistic social phenomena, rather than adopting practices based on singular perspectives and on potentially competing theories (Bolman & Deal, 2015). Berger (2000) suggested five core dimensions of organizational behavior—bureaucratic, collegial, political, symbolic, and systemic--which were similar to Bolman and Deal's four frames. According to Berger and Milem, who referred to earlier work of Bolman and Deal and their own work, reiterated that, "All college and university campuses are thought to exhibit aspects of all models of organizational behavior to some extent, yet each campus varies in the degree to which it fits each dimension" (p. 179).

Drawing on theories of organizational behavior, Berger and Milem (2000) developed an organizational impact model to explain multi-faceted organizational effects on student success outcomes. The model was designed to account for student input characteristics and experiences in college. Their research focused on the demographics of institutional structures (such as number of enrollments, admission requirements, public or private, and urban or rural) along with organizational behaviors (Franke, 2012). Their research hypothesized positive impacts on student success outcomes result from high student involvement. The organizational climate and its structures can directly influence the opportunities for students to have meaningful interactions. Positive outcomes on persistence, especially for students at greatest risk to progress, are realized when students are engaged in available curricular and co-curricular activities designed for student success (Arbona & Nora, 2007; Kuh, 2013).

Social Connectedness

Bean and Metzner (1985) focused their research emphasis on nontraditional students and argued that prior student retention research by Spady (1970), Tinto (1975), and Pascarella (1980) overemphasized the influence of individual student social characteristics on persistence (Seidman, 2012). They discovered that for nontraditional students, environmental factors have a greater influence when predicting student persistence. Future research on college completion by Bean (2005) illustrated the value of students being socially integrated with their institution and peers. Research on social connections made in college have demonstrated higher levels of individual resiliency and abilities to adapt to inherent academic and personal challenges (Roberts & Styron, 2010). Making social connections is a major part of the college experience. When these connections are made, students develop a sense of belonging to their institution and their academic community that positively contributes to rates of persistence and graduation (Chambliss & Takacs, 2014; Kuh & Love, 2000).

Student Involvement and Engagement

Schlossberg (1989) addressed marginalization issues students may experience because they are not being involved in college activities and programs. When students question whether they are a contributing member of their social fabric, they are at risk of developing feelings of marginalization, threatening their ability to persist (Roberts & Styron, 2010). Being engaged and involved in curricular and co-curricular activities, especially with peers, is important to student retention for under-represented populations (Huerta & Fishman, 2014; Schlossberg, 1989). In order to be meaningful, Schlossberg reiterated that, in order to be meaningful, institutionally designed and sponsored activities must promote social interactivity and engagement among peers, staff, and faculty members.

Pascarella and Terenzini (2005) determined that curricular activities designed to engage students with their peers not only reinforced the value of the learning environment, but also positively influenced other areas of academic life. Research has demonstrated that student participation in activities deliberately designed to promote engagement can positively impact persistence. However, individual student characteristics can have greater influence on the student success outcomes (Tinto, 1993). This reinforced that activities should be designed with the greatest potential for a positive impact on student groups at greatest risk to persist. “Maximizing retention and graduation of your students is key: providing programs and services that will help students succeed is fundamental” (Seidman, 2018, p. 45).

High Impact Practices (HIPs)

HIPs have been widely promoted and addressed as a successful way to improve student success (Kinzie & Kuh, 2017; Strategic Initiatives, 2018). However, there are narratives questioning whether HIPs are worth the investment and something that can be reasonably delivered at higher education institutions (Johnson & Stage, 2018). The AAC&U sponsored research to understand what promotes student success in higher education. This research resulted in a series of curricular and co-curricular HIP activities. Brownell and Swaner (2010) conducted a comprehensive examination of research on the impacts that first-year seminars, learning communities, SL, undergraduate research, and capstone experiences have on students. They explored impacts on participating students and looked for differences between various subgroups.

Brownell and Swaner discovered “the most common outcomes described for student participants include higher grades, higher persistence rates, intellectual gains, greater civic engagement, increased tolerance for and engagement with diversity, and increased interaction with peers and faculty” (p. 45).

Over the past decade, universities and colleges across the nation have been gradually implementing “purposeful pathways” (Leskes & Miller, 2006) for their students, including an integration of curricular and co-curricular applications of HIPs. However, how the practices are defined, delivered, and implemented across higher education, and even within individual institutions (Kinzie & Kuh, 2017) varied greatly (J. Kinzie, personal communication, September 17, 2019).

SL is a widely adopted HIP among institutions of higher education due to promotions from regional accrediting bodies and the well-known Kellogg and Carnegie foundations (Van Campen et al., 2013). There is a large body of evidence on the impacts of SL on students with a variety of positive outcomes including persistence and retention across all subgroup populations (Kuh et al., 2017; Mungo, 2017; Reed, Rosenberg, Statham, & Rosing, 2015). In addition, research has demonstrated that participating students benefit from an increased ability to reflect and understand coursework relevance in community practices (Sax, Astin, & Avalos, 1999).

The practice of SL has many possible permutations in design and delivery. The variability has presented a challenge to researchers attempting to understand the participatory impacts on student outcomes (Howe & Fosnacht, 2017; Kuh, 2008). Research issues described by Brownell and Swaner (2010) included challenges of managing moderating variables such as the characteristics of service experiences and self-selection bias. The issues presented are valid and have been somewhat mitigated by reducing the variability of moderating variables and following a standardized curriculum. Unlike its HIP counterparts, SL has a formal and recognized definition still in use today, “SL is a form of experiential education where students engage in activities that address human and community needs together with structured opportunities internally designed to promote student learning and development" (Jacoby, 1996, p. 5).

Even with its varying permutations, SL has become an established teaching strategy that bridges the academic classroom and local communities. It has become a widely adopted practice across the higher education landscape and is of particular interest to publicly funded institutions. Land-grant universities have evolved over time to include a strong component of community engagement as core to their mission profile (Gavazzi & Gee, 2018) and many institutions use SL as a mechanism to receive the Carnegie's classification for Community Engagement (Saltmarsh & Driscoll, 2015). Since its inception, SL teaching strategies have been rebranded as Community-Engaged Learning (Warren, 2012) while Jacoby's (1996) definition has continued to be the standard. Many institutions, including USU, require curriculum compliance with the standard to be recognized as a community-engaged learning (SL) course.

When Brownell and Swaner (2009) reviewed the research literature on SL outcomes they discovered, "that there is little research that looks at specific populations of students, and particularly underrepresented minority, low-income, and first-generation students" (p. 27). Their report identified various methodological reasons why there is still limited research on the impacts of SL, and especially on underserved student group populations, primarily self-selection bias and low numbers of student involvement.

A variety of challenges must be accounted for to accurately measure higher education outcome results. Students bring with them a rich set of experiences and individualized characteristics. Institutions provide dynamic environments with various structured and spontaneous options that may influence success outcomes. As previously outlined in this chapter, mitigating these challenges has been accomplished by prominent researchers who developed methods to defend theories and established a foundation on which to build. Recognizing this foundation provides an opportunity for future research that employs innovative methods to continue discovering what works in higher education. Maki (2017) concluded her research on assessment of academic programming by stating, “Assessment is higher education’s ethical commitment to our currently enrolled students, [and] it takes place continuously in the present tense” (p. 169). Understanding the timely impacts of intentionally designed experiences like SL provides administrators, faculty, staff, and students the ability to reflect on whether their contributions may have produced student successes or failures as measured by the outcomes.

Student Outputs

The student outputs section provides a review of literature supporting quasi-experimental research methodology. When following Astin and Antonio’s (2012) IEO model to assess impacts of environmental activities on student outputs (Figure 5), researchers must isolate the activity from all other potentially confounding student variables, such as managing for self-selection bias (Brownell & Swaner, 2009). The validity of measured student outcomes depends on the “statistical gymnastics necessary to isolate the experience as the only differentiating variable between groups of participating and non-participating students” (G. Gee, personal email, July 10, 2017).

Methods of experimental research employ randomized control trials (RCT), which are considered the gold standard for establishing causal links between treatments and outcomes. RCT have proven to manage self-selection and offer the most unbiased research estimates (Rosenbaum & Rubin, 1985; Rubin, 2008). The integrity of experimental research methods requires randomly assigning students to research groups. It also requires a significant amount of resources and time, whereas quasi-experimental research require large amounts of archival data and leverages

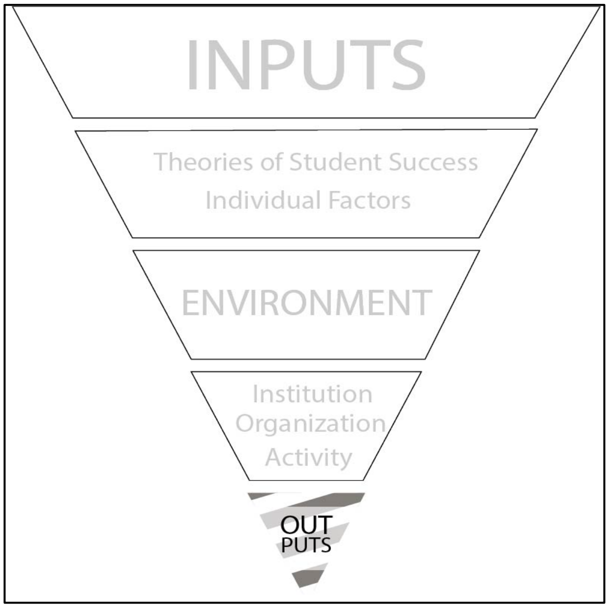

Figure 5. Student outputs.

computational power to reduce time and potentially invasive techniques (Blaich & Wise, 2010). Nevertheless, when using nonexperimental data, one of the greatest threats to research validity is how self-selection bias can adversely impact the ability to estimate defensible causal inferences about the treatment (Brownell & Swaner, 2009; Franke, 2012; Graham & Kurlaender, 2011). An alternate, and often more feasible, method to a randomized control trial is a quasi-experimental design using covariate matching techniques to compare similar looking individuals exposed to a treatment with those who were not (Brooks & Ohsfeldt, 2013).

Covariate Selection, Segmentation, and Matching

To reduce bias, extensive segmentation and matching techniques depend on properly selected covariates that have optimal properties used for predicting student persistence to the next term (Astin, 1970; Astin & Antonio, 2012; Newcomb, 1973). Propensity score matching (PSM), formalized by Rosenbaum and Rubin (1983), has grown in its popularity when conducting quasi-experimental research in the fields of medicine, healthcare, and education (Giani, Alexander, &

Reyes, 2014; Melguizo, Kienzl, & Alfonso, 2011; Soria, Laumer, Morrow, & Marttinen, 2017; Wang et al., 2013).

However, some researchers have challenged the validity of PSM and posited that limitations were found when certain covariates were not used to match analyzed individuals (Brookhart et al., 2006). Their research suggested that it is always necessary to include additional variables unrelated to the treatment and it's the outcomes. Referring to Astin and Antonio's (2012) IEO model, Brookhart et al. would assign propensity scores that included variables known to influence student outcomes such as student input characteristics and environmental behaviors. They found that including outcome-related variables did not increase bias but did significantly decrease the variance of estimated treatment effects. They also provided additional cautionary insights to avoid using "standard model-building tools to create good predictive models of the exposure [as it] will not always lead to optimal propensity score models, particularly in small studies" (Brookhart et al., 2006, p. 1149). Brookhart et al.'s (2006) study illustrates an important, yet potentially resource intensive, strategy that suggests including large numbers of covariates and customized predictive modeling to best represent the analyzed populations (Shrier, Platt, & Steele, 2007).

Methods of segmentation and matching models were used in this study with hundreds of student-level covariates extracted from university sources and categorized by the following characteristics: academic performance, degree progression metrics, socioeconomic status, and online course engagement metrics (Kil, Chan, et al., 2017). Using the regularized ridge regression statistical technique, each available covariate associated with students were eligible for analysis and prioritized. The covariate was then rank ordered by their predictive power (Allen, 1974; Demir-Kavuk, Kamada, Akutsu, & Knapp, 2011) and used to derive predicted persistence scores for analyzed students. The methods for study leveraged an existing predictive model, customized for USU, that provided predetermined student covariates optimized to predict a student's propensity to participate in an activity along with a student's prediction to persist to the next term. The methods used to calculate the derived scores were designed to account for potentially small numbers of participating and control populations (D. Kil, personal email, August 19, 2017) and thus accounted for one of greatest challenges for assessing SL (Brownell & Swaner, 2009).

Prediction-Based Propensity Score Matching (PPSM)

Using derived prediction and propensity score values for pilot and control groups, students were matched through a recently developed and patented method called prediction-based propensity score matching or PPSM (Kil, Derr, et al., 2017; Kil, Shin, & Pottschmidt, 2004). The uniquely designed PPSM methods were published in a 2017 US patent titled *Student Data-to-Insight-to-Action-to-Learning Analytics System and Method* by Civitas Learning, Inc. (see Appendix C) and have been proven to statistically match segmented groups of students for purposes of rapid analysis and evaluation (Kil, Derr, et al., 2017). Figure 6 illustrates a pre- and post-comparison example where PPSM is used to match segments of pilot and control students.

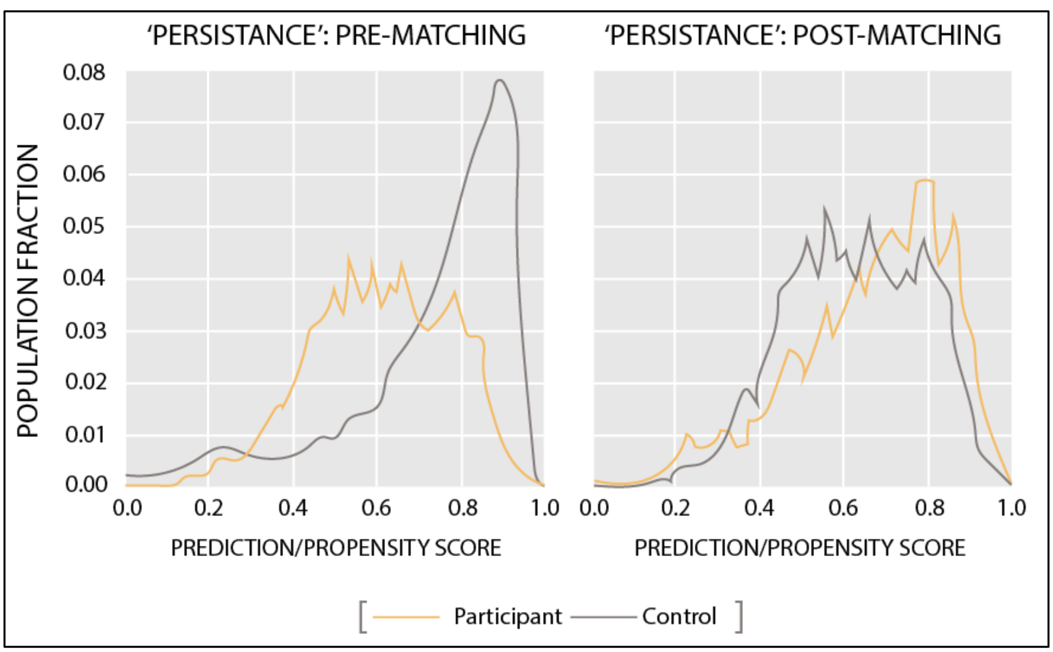

Figure 6. Pre and post matching of analyzed students.

The comprehensive PPSM methods statistically match students who are, “equally likely to succeed and equally likely to receive the treatment” (Kil, Chan, et al., 2017, p. 3), and thus remove potentially confounding effects of bias into the outcomes.

Because of its dependence on statistical power, the accuracy of PPSM segmentation and matching models, as illustrated in Figure 7, can be adversely affected by pilot and control group population sizes. PPSM attempts to match student pilot and control groups based on derived prediction and propensity score covariates. Based on preliminary power analysis results for this study, sample sizes of $N < 250$ risk losing the necessary statistical power that can be lost when groups cannot be adequately matched.

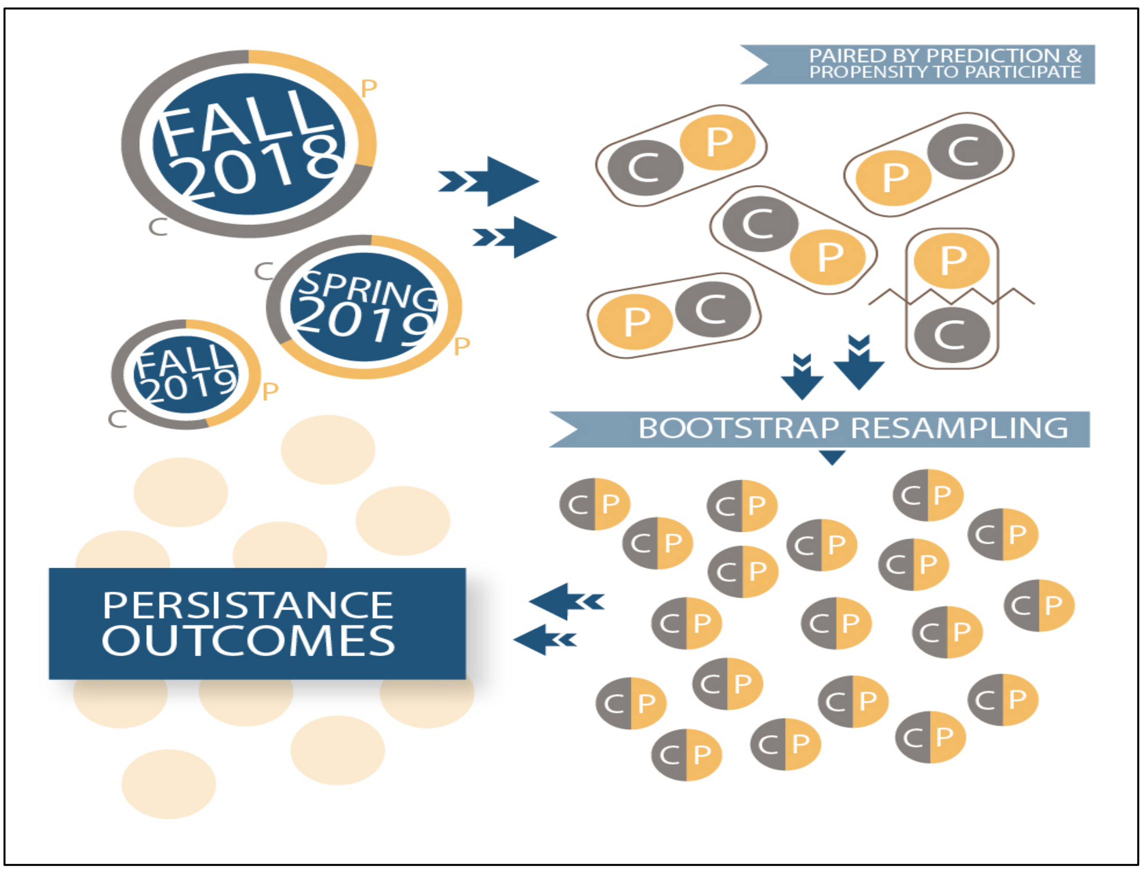

Figure 7. Estimating persistence outcomes for participating students.

The student outcome effects of loss in statistical power were identifiable in consequent *p* values and confidence intervals. The PPSM matching methods were designed to provide optimal results for both large and small populations sizes by using pre-determine caliper widths (Kil, Chan, et al., 2017). Consequently, different student outcome results, discussed at greater detail in Chapter III, needed to be interpreted through a careful comparison of p-values, confidence intervals, and matching percentages.

To eliminate confounding factors when using PPSM, a data-intensive and multi-step process of segmentation and matching was followed. The use of a logistical ridge regression was employed to identify optimal covariates used to (1) determine a student's predicted score to persist to the next term and (2) determine a student's score that designates their propensity to participate in the activity. The two predictor variables of persistence and propensity were used in an iterative process of matching and resampling.

The PPSM method paired pilot and control students based on their individually derived propensity scores to participate in the activity and prediction to persist to the next term. For this study, accuracy of matching was accomplished through a nearest neighbor method using a standardized caliper width of .05 intended to eliminate 95% of the bias (Soria et al., 2017; Wang et al., 2013). The PPSM methods employed in this study matched students without replacement, meaning that each student had to be included in one or more bootstrap iteration. Otherwise, unmatched students were thrown out of the analyzed population.

The selected caliper width used in this study was selected to account for possible covariate imbalances (Rubin, 2008). "The choice of caliper width should reflect the variance-bias trade-off: using narrower calipers will result in the matching of more similar subjects" (Austin, 2011, p. 150). However, reducing caliper widths to match similar pilot and control students without replacement could have dramatically decreased the population of matched students and negatively impact statistical significance.

PPSM leveraged the brute force of machine learning for bootstrap resampling iterations to determine a mean value that most closely represents the population to eliminate possible bias (Caliendo & Kopeinig, 2008; Hall & Martin, 1988). The method of bootstrap resampling took random sample iterations from a pool of control students and attempted to match them with the pilot population (Austin, 2011). The resampling process determined a mean value that was statistically representative of the population and calculated a respective confidence interval.

Summary

The aforementioned theories have provided a comprehensive way to explain how individual student input characteristics can influence student persistence and degree completion. As illustrated in the literature, when measuring the effects of student success activities, researchers must consider individual characteristics and experiences students bring to college, as they potentially influence student outcomes. The IEO model used to guide this study incorporates student background characteristics as inputs used to group individuals for analysis. A quasi-experimental research design used for this study employed a state-of-the art learning analytics infrastructure to conduct PPSM methods. The methods were designed to support student characteristics that may contribute or inhibit whether a student will persist. Lastly, the reviewed literature presented models for student success in higher education based on researched theories and practices and will be used to guide discussion topics in Chapter V of this study.

CHAPTER III

METHOD

To understand the impacts of extant student activities on their students, education leaders and scholars require methods to evaluate activity effectiveness. Using historical and observational data, the quasi-experimental research methods used for this study were designed to isolate the influences of an extant activity on term-to-term student persistence. The methods employed a multi-step approach using machine learning for rapid evaluation and advanced statistical techniques.

The purpose of this study was threefold: First, to advance knowledge regarding the localized effects on persistence to the next term for students who participated in the HIP of SL at USU. Second, to examine the impacts of persistence for subgroup populations of students who participated in SL activities. Third, to extend the most recent scholarly efforts on student success by demonstrating the efficiency of using an advanced computational framework of learning analytics to examine the impacts of extant activities on local bodies of students.

Conceptual Model

Guided by the conceptual IEO model (Astin & Antonio, 2012), the quasi-experimental research methods for this study estimated the effects of participating in HIP activities within the educational environment on student outcomes. By using large sets of observational data, this study applied the state-of-the art statistical PPSM method to account for student input characteristics that could potentially contribute to or confound student success outcomes (Astin, 1993; Astin & Antonio, 2012).

The PPSM methods uses a combination of derived variables of scores including an estimation of an individual's propensity to participate in an activity and an estimation of an individual’s likelihood to persist to the next term. PSM methods used in this study were developed by Rosenbaum and Rubin and are commonly used methods for quasi-experimental research to manage self-selection bias (Rosenbaum & Rubin, 1983, 1985; Rubin, 1976, 2008). Combined with an estimated predicted persistence score, developed by Kil, Shin, and Pottschmidt (2004), the study leveraged vast quantities of individual covariates to derive a predicted persistence score as an uber-variable to represent student input characteristics. Through the use of a powerful machine-learning infrastructure that combined the estimation scores for PPSM methods on observational data, this study was able to rapidly analyze the impacts that extant SL activities had on a local body of students at USU.

Research Questions and Hypotheses

The intent of this research was to determine the treatment effects of HIP SL activities by comparing groups of participating students with control students (those who do not participate). More specifically, the research investigated the influence of SL courses on student persistence to the next term. It also investigated the impact of SL on categorical groups of students enrolled in either upper or lower division courses.

The following three research questions guided this study.

1. Does participation in the curricular high impact practice of service learning have a significantly positive difference in the means on students’ likelihood to persist to the next term?
2. Is there a significant difference in the student persistence mean values based on service learning course levels (e.g., lower division or upper division)?
3. Do the difference in student persistence mean scores vary based on subgroup populations of students who participate in the curricular high impact practice of service learning?

Each research question was analyzed independently and not disaggregated from an overarching analysis. In other words, question one investigated the impacts on all students available for analysis, whereas questions two and three categorically separated populations of upper and lower division course participants. In addition, question three independently analyzed each subgroup using students that only correspond with their respective population.

Hypothesis I (H_1) Difference in Difference Effects of Participation in SL Activities

According to theories of persistence and degree completion addressed in the previous chapter, participation in a HIP activity categorized by SL is generally hypothesized to positively influence student persistence to the next term at higher education institutions (Kuh, 2013). The interpretation of how to design and deliver the HIP activity varies by institution and may thus impact student persistence differently. However, due to the hypothesized effect of participating in a HIP, it is assumed to increase a student's persistence likelihood despite the potential differences of implementation.

The null hypothesis of (H_1) states: There were no positive differential effects on persistence to the next term for student participants of SL activities at USU.

Hypothesis II (H_2) Difference in Difference Effects of Lower and Upper Division Student Participations in SL Activities

When assessing students in higher education, Astin (1970) recommends differentiating sampling groups by freshmen/sophomore (lower) and junior/senior (upper) divisions of students for greater accuracy. To measure the difference in effects for each division, this study grouped students in 1000- and 2000-level participants as "lower division" and 3000 and 4000 course participants as "upper" division.

The null hypothesis of (H_2) states: There were no differential effects on term-to-term persistence between groups of upper- and lower-division student participants of SL activities at USU.

Hypothesis III (H_3) Difference in Difference Effects of Participation in SL Activities for Subgroup Populations of Students

Given the empirical evidence on the influence of student input characteristics on student outcomes, it is hypothesized that categorical measures of student subgroups (e.g., terms completed, part-time, first-time in college, etc.; see Appendix A) had differential effects resulting from participating in a HIP activity. It was thus hypothesized that categorical student subgroups illustrated different effects on persistence to the next term for participating students.

The null hypothesis of (H_3) states: There were no differential effects of categorical subgroup populations on persistence to the next term for students participating in SL activities at USU.

Analytic Approach

This study examined student participation of activities designed to positively impact success in higher education. The methods for this study estimated links between treatments and expected student outcomes using historical and observational student data. More specifically, this study determined the estimated impacts on persistence to the next term for students who participated in courses with a qualified SL curriculum. USU has an established set of criteria that professional staff in the Center for Community Engagement and respective faculty used to qualify courses analyzed for this study (see Appendix B).

Quasi-Experimental Design

A quasi-experimental research design was used to analyze historical and observational data from participants of extant college activities. Statistically indistinguishable groups of participant and control students were analyzed to determine comparison results. Using PPSM methods, each analyzed participant was matched to reduce potential selection and participation bias. By using these methods, it was possible to statistically isolate the effects of the SL activity on participating students compared to their relatively identical counterparts. The result of PPSM isolated participation in the activity as the differentiating variable between the participant and control groups of students, thus providing a comparison of respective outcome differences (Kil, Chan, et al., 2004; Melguizo et al., 2011).

Methodology

Figure 7 (see Chapter II) illustrates the PPSM statistical processes used to estimate impacts on student persistence to the next term. The illustration communicates a logical and linear multi-step process, but in practice the steps were simultaneously conducted and include the following: (1) aligning individual participating students to an activity during a respective timeframe; (2) creating a pool of control (nonparticipating) students who had an equal opportunity to participate in the activity as the participating students; (3) performing a matching process for the pool of control and participating students to ensure they are statistically indistinguishable by using data footprints of derived individual variables and; (4) executing statistical hypothesis testing to determine a significant difference between the actual persistence of participant and control groups (Kil, Chan, et al., 2004, 2017).

The following sequence in Table 2 illustrates the five statistical steps that were followed to determine criterion outcome values for each of the research questions: (1) using a multivariate logistical regression, assigned a predicted propensity to participate score to every student in the analyzed population; (2) using a multivariate logistical regression, assigned a predicted persistence score to every student in the analyzed population; (3) following PPSM methods, matched statistically indistinguishable students using their predicted persistence and propensity scores under constrained parameters though a fixed caliper width; (4) using bootstrap resampling methods, calculated persistence prediction mean scores for participating and control groups of students that most closely represents the analyzed population; and (5) using a statistical Z-test, calculated difference in differences between respective group mean scores of predicted and actual persistence to the next term.

Table 2

Five Statistical Steps to Determine Criterion Outcome Values

Step	Statistical method
1. Derive propensity to participate scores	Multivariate logistical regression
2. Derive estimated persistence scores	Multivariate logistical regression
3. Match individuals from student groups	Restricted caliper width
4. Calculate estimated prediction mean scores	Bootstrap resampling
5. Calculate outcome differences	Difference in differences

These methods were primarily used to reduce self-selection bias by removing potential confounding features related to the outcomes. To reduce this bias, this study employed PPSM methods. Derived estimator scores of a student's propensity to participate in an activity and their prediction to persistence to the next term are required for PPSM. When using PSM, Steiner, Guo and Frasier (2010) suggest using weighted scores. For this study, weighting of individual student-level covariates is accomplished by applying salient machine learning to determine regression coefficient estimates. The beta coefficient estimates were assigned to each available student-level covariate through the process of L2 regularized ridge regression (Brookhart et al., 2006; Demir-Kavuk et al., 2011). When the ridge regression calculations were complete, values of beta coefficients were stored for use in regression models to derive propensity and persistence scores.

Individual propensity scores are known values when conducting randomized control experiments. For example, if a simple experimental design had been used for this study, analyzed participant and control students would have receive an equal 0.50 propensity score because half of the students would have been selected to receive a treatment. Whereas, this study used a quasi-experimental, or non-randomized methods, where propensity scores were unknown and had to be estimated. Estimations were accomplished by using a multivariate logistical regression model. Rosenbaum (2010) and Rubin (1997) recommended "using all available covariates…to maximize the precision an accuracy of the estimated propensity scores" (May, 2012, p. 500). This study used PPSM methods invented by Kil, Derr, et al. (2017) that employed a proprietary whitelist of 50 student-level covariates for propensity score modeling from the following categorized features, "Incoming factors, academic performance, progress towards degree, financial aid/ socioeconomic status (SES), and engagement activity" (p. 7).

The theoretical regression model used to derive an estimated propensity to participate score is described as:

$$\widehat{PS} = a + b_1\chi_1 + b_2\chi_2 + b_i\chi_1 + e$$

where the estimated propensity score $\widehat{PS}$was calculated using independent variables χ, such as demographics, academic performances, socioeconomic status, etc., and their beta coefficients *b*.

As previously mentioned, PPSM required the use of derived scores for both propensities to participate and predicted persistence. Deriving predicted persistence scores required approximately two times more covariates than what was used to estimate propensity scores. The regression model to derive predicted persistence scores used a proprietary whitelist of approximately 100 student covariates and associated beta coefficients available for each analyzed student (Kil, Chan, et al., 2017).

The theoretical regression model used to derive a predicted persistence score is described as:

$$\widehat{PP} = a + b_1\chi_1 + b_2\chi_2 + b_i\chi_1 + e$$

where the predicted persistence score $\widehat{PP}$ is calculated using independent variables χ, such as demographics, academic performances, SES, etc., and their beta coefficients b.

A bootstrap resampling method was used to accomplish two primary outcomes: (1) calculate mean values of persistence for both participant and control groups and (2) derive confidence intervals associated with estimated persistence outcomes. The resampling methods were used to derive predictive persistence and propensity score values to pair students from their respective groups. The bootstrap methods used a proprietary set of functions designed by Civitas Learning, Inc. (Kil, Chan, et al., 2017) and were an implemented feature of their Impact statistical software package. The bootstrap resampling functions adhered to open source methods found in the following available text: *BootES: An R Package for Bootstrap Confidence Intervals on Effect Sizes* and *An Introduction to Bootstrap Methods with Applications to R* (G. Gee, personal email, June 12, 2019). Gee further explained that Impact limited bootstrapping parameters to 30 iterations, which Civitas Learning, Inc. had determined as a fixed number of samples sufficient for most analyses and balances product performance and computational efficiency. Testing the predictive model used for sampling can be accomplished by measuring an error greater than $\pm$ 3% from the actual persistence of control groups of students to the estimated counterfactual value (G. Gee, personal email, December 14, 2018). Consequently, for this this research study, analyzed groups that failed the predictive model test were not considered valid for interpretation. Prior to interpretation, each analyzed group was tested for significance and predictive model validity. For example, when significant results were $p < 0.05$ with an error $> \pm 0.03$, results were not considered for interpretation.

The final methodological step to estimate outcome impacts used mean score values of persistence calculated through the aforementioned functions of bootstrap resampling. To develop a distribution of group values, predicted persistence and propensity score outcomes of each analyzed student successfully paired with a counterpart was plotted. Using respective group distributions, mean score values were used to calculate the differences between the two groups. Difference in values were finally calculated using a standardized z-test.

The theoretical z-test used to derive predicted persistence outcomes is described as:

$$PP = \frac{\hat{X} - \bar{X}}{\sigma}$$

where the predicted persistence outcome PP is calculated using predicted persistence mean $\hat{X}$ values, minus actual persistence mean $\bar{X}$ values, divided by sigma σ. For final analysis, the resulting predicted persistence was calculated as a standardized *z* score and was converted to a percentage value to represent the difference percent between mean values. Lastly, corresponding confidence intervals were derived from the bootstrap resampling calculations and were used to determine the significance of the outcome results.

Transformation of Data

Individual input characteristics associated with each analyzed student were used to match a student who participated with his or her statistical twin who did not. Outcome measures for this study were term-based and thus required all student data be associated with a respective term. Both groups of students eligible for analysis were aligned by the same term and had an equal opportunity to participate in a SL (Allen & Dadgar, 2012; Nosaka & Novak, 2014; see Figure 8).

Participant Data

Student participant data for SL activities was drawn from the university's SIS student module. Individual students available for analysis had an assigned university identification number, which for USU was their A-number. The identification number was the unique identifier found in each system of record and used to align historical data sets with the respective students. A multivariate logistical regression used individual covariates to derive predicted persistence and

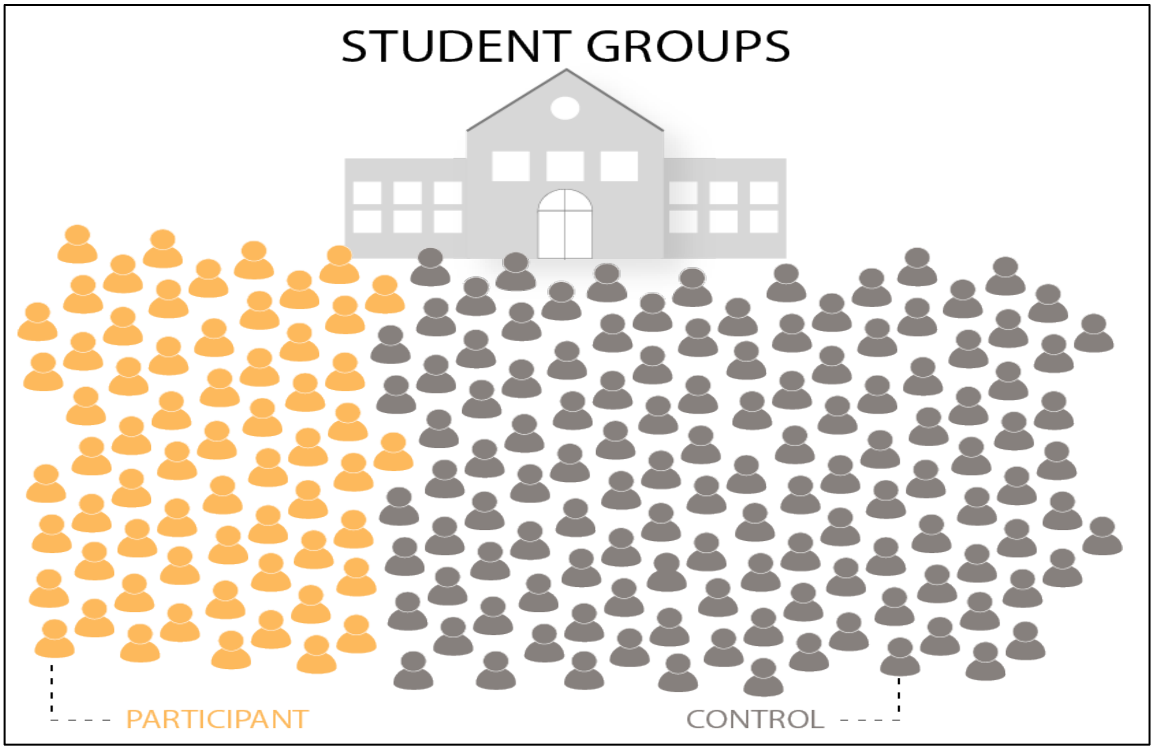

Figure 8. Analyzed participant and control groups of students.

propensity scores used for PPSM. The covariates used in this study aligned with prominent research models used to predict student success (Seidman, 2012; Kuh, 2013; Kuh et al., 2017; NSSE, 2013a; Tinto, 2012).

Participant data used in this quasi-experimental research design were identified from convenience samples of USU students and were identified by extracting term-based course enrollments from over 254 courses designated as SL. The participant group consisted of 8,959 students who voluntarily took SL courses during the one of six terms: Spring 2016, Fall 2016, Spring 2017, Fall 2017, Spring 2018, and Fall 2018 (see Table 3). To optimize resources, this study limited its analysis to 3 years and 6 terms of participant data. The selected terms provided an adequate number of students' data to analyze for significant statistical outcomes and meaningful effect sizes.

Table 3

Students Available for Analysis

n	Student group	Term	Lower courses	Upper courses	All courses
1,092	Participating group of students	Sp. 16	4	24	28
17,519	Control group of students	Sp. 16	-	-	
976	Participating group of students	Fa. 16	3	20	23
18,574	Control group of students	Fa. 16	-	-	
1,594	Participating group of students	Sp. 17	11	36	47
17,290	Control group of students	Sp. 17	-	-	
1,566	Participating group of students	Fa. 17	3	34	37
18,736	Control group of students	Fa. 17	-	-	
2,030	Participating group of students	Sp. 18	14	48	62
17,310	Control group of students	Sp. 18	-	-	
1,701	Participating group of students	Fa. 18	7	50	57
18,909	Control group of students	Fa. 18	-	-	
8,959	Participating group of students	6-Terms	42	212	254
108,338	Control group of students	6-Terms	-	-	

Summer term participants were excluded from this study due to small numbers of available participant data, and because the predictive modeling used for this study was limited to predict term persistence from only spring to fall and fall to spring.

A pool of control (nonparticipating) students was identified as individuals who had an equal opportunity to participate in SL courses during the same academic terms as the participating students but did not participate; there were 108,338 students available for the control group. Students available for comparison were not mutually exclusive for each term. Answering research H_1 required that none of the control students had ever participated in a SL course. As such, students who had previously participated in a USU SL course were removed.

For research H_2 and H_3, students enrolled in lower division (1000- and 2000-level) courses and upper division (3000- and 4000-level) courses over the 6 university terms were categorically separated for analysis.

Table 4 shows the study's detailed demographics. The average ethnic diversity of undergraduate students at USU during the fiscal years of 2016, 2017, and 2018 were 82% White or Caucasian. The remaining students were predominantly Latino and Hispanic (6%), while other ethnic groups are relatively equally dispersed. Notable subgroup differences at USU can be categorized by gender. Gender differences of overall enrollments was 47% female and 53% male. During the research timeframe, 37% of females and 31% of males who attended USU were part-

Table 4

USU Student Demographics, 2016 to 2018

Subgroup	2016 %	2017 %	2018 %	3-yr avg %	3-yr avg % (Males)	3-yr avg % (Females)
Face to face	80	81	81	81	86	76
Broadcast	21	21	22	21	42	58
Blended	5	5	4	5	45	55
Online	32	33	35	33	38	62
Full-time students	65	66	66	66	69	63
Part-time students	35	34	34	34	31	37
First time in college	18	18	19	18	18	19
Female	47	47	46	47	-	53
Male	53	53	54	53	47	-
Hispanic or Latino	6	6	6	6	5	7
Two or more	2	2	2	2	2	2
Other unspecified	5	4	4	4	4	4
Asian	1	1	1	1	1	1
Black or African American	1	1	1	1	1	1
Pacific Islander	.35	.35	.35	.35	.35	.35
American Indian/Alaskan Native	2	2	2	2	1	2
White or Caucasian	81	82	83	82	82	81

Utah State University (n.d.a.). Retrieved from the Office Analysis, Accreditation and Assessment website: http://www.usu.edu/aaa/enrollmentsataglance.cfm time students. And students taking broadcast courses at the university could be similarly described with 23% of all females and 19% of all males selected those options.

Data Protection

A quasi-experimental research design was followed for this study using historical (archival) and nonexperimental student data. Individual student lists intended for analysis were not made available to the researcher. Digital files containing student A-numbers, term dates, and their respective participating groups were prepared by an honesty broker, a professional staff of USU's Center for Student Analytics (CSA). The honesty broker uploaded prepared files to the Civitas Impact statistical analysis software. Once the individual student data files were submitted, neither CSA staff members nor local university administrators of the Civitas software were able to access them. After the Civitas Impact software application had performed its PPSM algorithms on the submitted files, the outcome information in the form of flat files were used for analysis. The researcher did not have access to any individually identifiable information.

To ensure appropriate protection of human subjects, a research protocol was submitted to USU's institutional review board office. The protocol was approved on July 9, 2019. Data analysis was not conducted prior to approval.

Data Analysis

Data files were prepared by USU's CSA employees, with aligned term-based timestamps for both participant and control groups of students and were submitted to the Impact statistical software by Civitas Learning, Inc. where the PPSM methods were employed. The software produced flat files containing analyzed populations in aggregate with matching similarity percentages, overall and term-based differences in difference outcomes, p-values representing statistical significance results, and corresponding confidence intervals. Using R-studio, the resulting flat files were systematically analyzed and converted into visual representations (figures) and tables for final analysis of research questions $H_1\mathrm{H}_1$, $H_2\mathrm{H}_2$, and H_3.

Each research question was independently analyzed to determine the following outcomes: (1) aggregated change in persistence for the analyzed population; (2) aggregated change in persistence categorized by each term available for analysis; (3) total number of students available for analysis including both participating and control groups; (4) percentage of participating students available for analysis; (5) percentage of statistically matched students that were not thrown out of the analysis during the process of bootstrap resampling; and (6) criterion outcomes for each subgroup of students including difference in difference, confidence intervals, and *p* values.

Interpreting Difference in Difference Criterion Outcome Values

Difference in difference is a popular estimator technique that uses observational data to mimic experimental research design and estimate the effects of interventions (Abadie, 2005; S. O. Becker & Ichino, 2002). Figure 9 shows difference in difference results were calculated by statistically comparing the estimated population means from bootstrapped iteration distributions of the predicted persistence rates with the actual persistence rates of participating and control groups of students. The resulting criterion variable represented an estimated impact of persistence to the next term with a respective confidence interval and measure of statistical significance. For this study, statistical significance for criterion values were limited to p values < 0.05.

The criterion outcome values of difference in difference for each research question were used to test H_1, H_2, and $H_3\mathrm{H}_3$ in this study. Figure 9 provides graphic representation example of predicted and actual values used to determine the estimated outcomes. In the sample data illustrated in Figure 9, notice the closely plotted prediction values of the participant and control groups. Figure 10 illustrates a restricted caliper width used in bootstrap resampling iterations. If

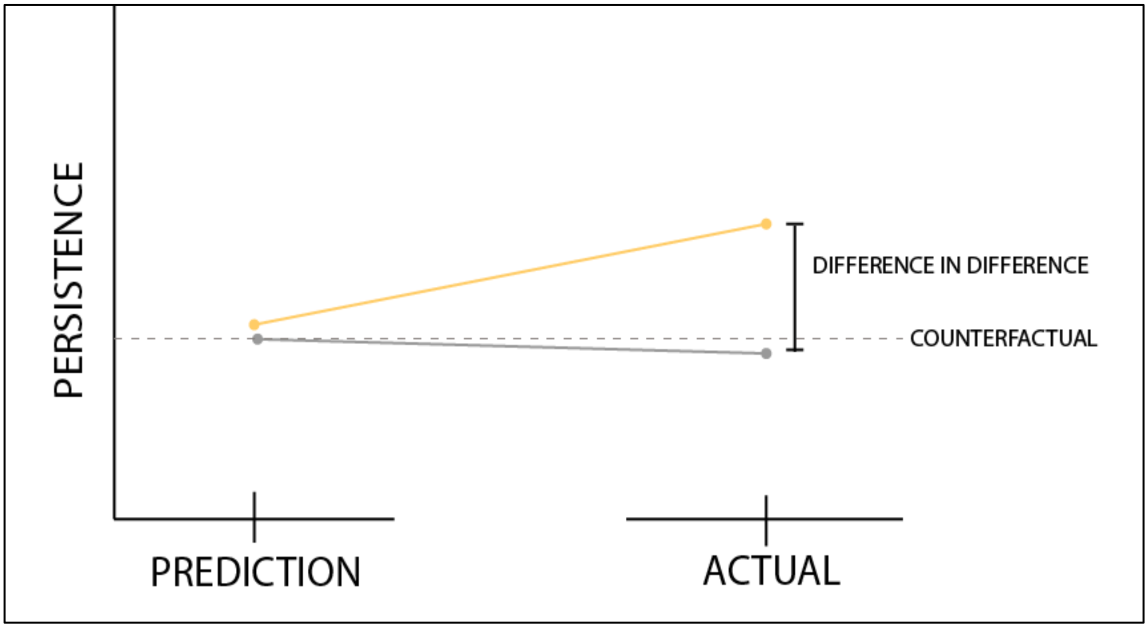

Figure 9. Difference in difference persistence outcomes.

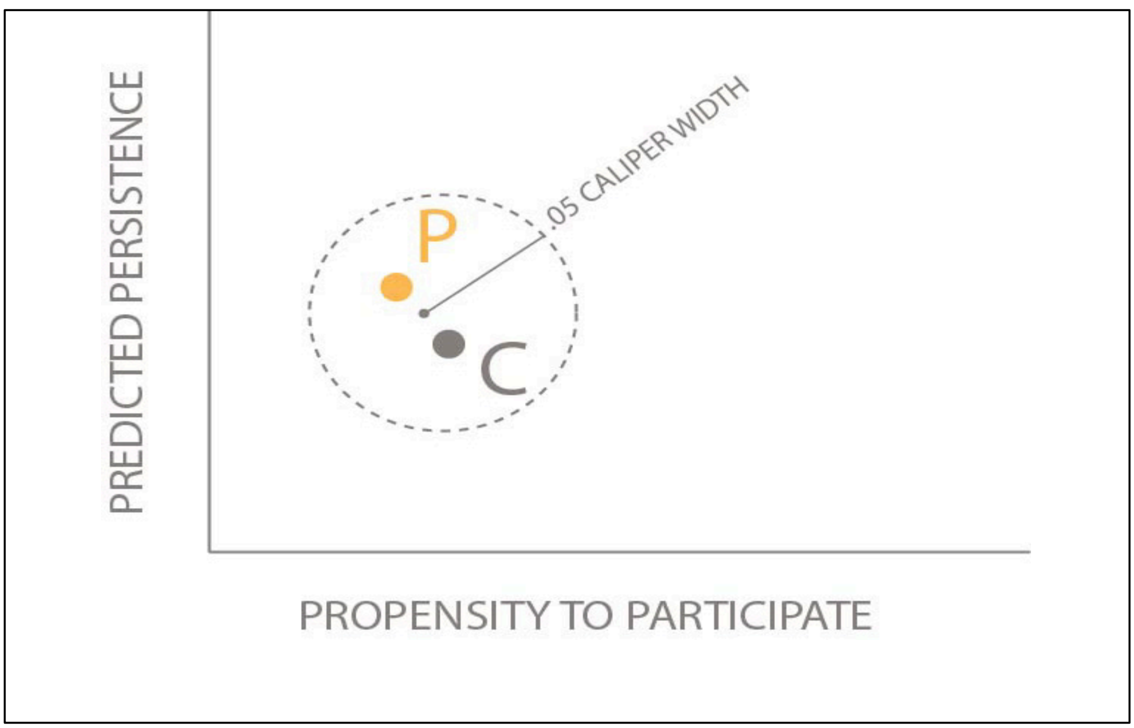

Figure 10. Restricted caliper width when bootstrap resampling.

more than one control student fell within the caliper constraints, one of those students was randomly selected. The other was thrown out and then made available for matching in other bootstrap iterations.

The matching process estimated mean values that most closely represent the analyzed populations with relatively close mean values of both control and participant groups, as visually represented in Figure 11.

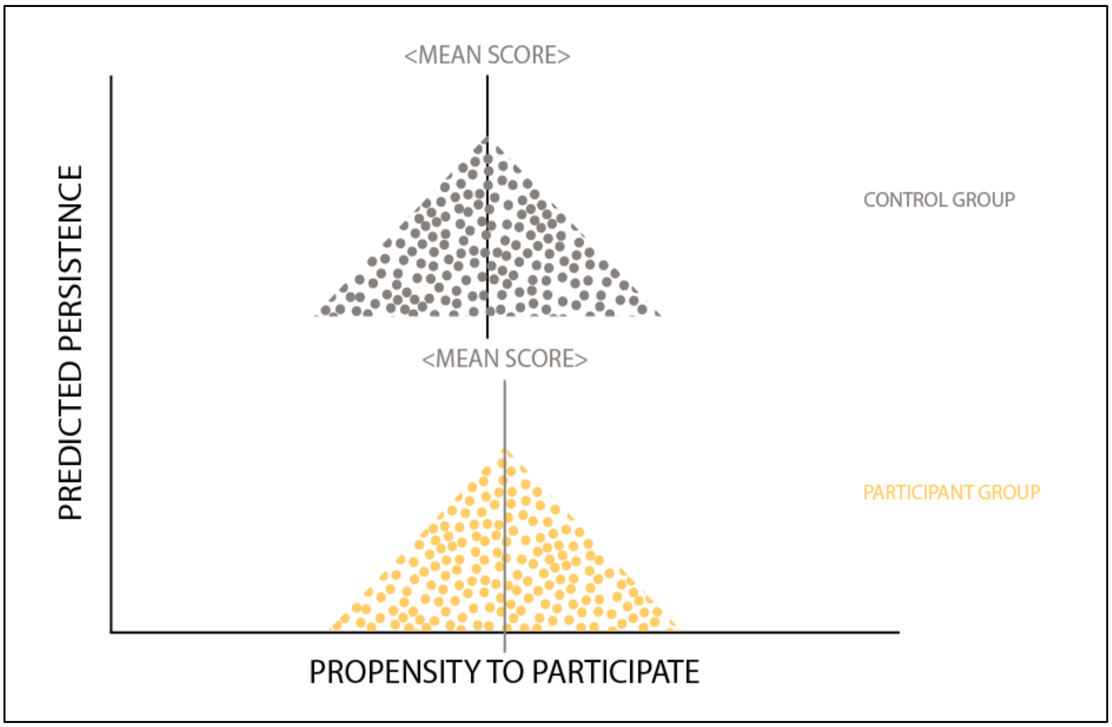

Figure 11. Histogram plots of matched students.

This study's matching methods were designed to reduce endogeneity bias that could have inadvertently been introduced into the predictive models (Menaldo, 2011). Each individual available for analysis received a persistence score derived from customized predictive models designed for USU. Precise student matching depended on the accuracy of the predictive models. However, if eligible comparison groups of participant and control students had "significantly different student populations and features, the current persistence prediction models may no longer be accurate for some of the historic terms" (G. Gee, personal email, December 14, 2018). The example data in Figure 9 is an estimated representation of a counterfactual value for the predicted persistence of the two groups. Detection of model inaccuracies could have been identified when an error of the actual student persistence value was greater than $\pm$ 3% of the estimated counterfactual (G. Gee, personal email, December 14, 2018). If an error was detected, the predictive model would have been recalibrated with the most current student data. A visual representation of the actual persistence outcomes and the estimated counterfactual value provides a quick analysis to determine the models' accuracy.

Aggregated Change in Persistence

Aggregated changes of persistence metrics were used to illustrate an executive summary of the treatment effects on participating students. The executive summary of statistics included: (1) an overall percentage of change in persistence with corresponding confidence values, (2) an overall change in students retained per year with corresponding confidence values, (3) the academic terms the treatment was available for analysis, (4) the total number of participating and control students available for analysis, (5) the number of participating and control students matched for analysis, and (6) the percent of students matched for the analysis.

Aggregated Change in Persistence by Term

Each study research question was analyzed using a bar graph that represented difference in difference values for each available term. The visual representations using analysis results was intended to communicate the following: (1) the overall change in persistence including all terms, (2) statistical significance results for each term analyzed, and (3) outcome trends for comparable terms, such as Spring to Spring or Fall to Fall.

Subgroup Change in Persistence

Each student subgroup was independently analyzed to determine difference in difference persistence outcomes (see Appendix A). Analyzed students were categorized into a respective subgroup and matched with statistically identical counterparts from the available the participant or control group. Summary statistics for each subgroup was organized in a table to answer H_3 and included: (1) the sample size of students available for analysis, (2) a subgroup category title, (3) the actual percentage of persistence of the participant group, (4) the actual percentage of persistence of the control group, (5) the percentage of difference between participant and control groups, (6) the confidence interval percentage, and (7) the corresponding p-values for each analyzed subgroup.

Individuals included in subgroups were not be mutually exclusive. For example, an individual could have been a female, White, and a full-time student. Summary statistics, like the overall change in persistence, were calculated using the difference in difference methods as previously described. Further interpretation of data was visually organized using a table with corresponding subgroups and difference in difference outcomes.

Subgroup results were dependent on data sets with an adequate number of comparable participant and control students. Subgroups with fewer than 250 students were considered too small to adequately match individuals and were not considered reliable for analysis (Kil, Chan, et al, 2017). See Appendix A for a comprehensive list of possible student subgroup categories and corresponding definitions.

Missing Data

The organization of historical student-level data intended for this study had undergone rigorous cleaning and verification for missing data checks by USU’s Office of Information

Technology, Office of Analysis, Accreditation, and Assessment, and the CSA. The Civitas Learning, Inc. analytical software package, used to perform PPSM methodology, had been collecting and updating archival data by following a rigorous data schema on 24-hour intervals since 2016. The university's Office of Information Technology has maintained a SIS and ensures its respective data as accurate and current. Select student-level covariates used in this study were refreshed weekly. Derived persistence prediction scores had been calculated weekly for each participating and control student, stored in a data base, and were made available for this study. The derived persistence prediction scores used optimal covariates relative to the university's predictive model. As a result, the model will have adapted and accounted for missing student-level covariates.

The custom predictive persistence model designed for USU by Civitas Learning, Inc. accounted for students who reported leaves of absence (LOA). The predictive model had been especially designed to not be adversely affected by large groups of students who intentionally stopped attendance for a variety of reasons, such as military or religious service. The predictive models used in this study to derive scores of persistence had been calibrated to account for the institution's unique LOA populations.

Primary impacts that potentially resulted from missing data in this analysis was verified in the matching process. The methods employed the statistical technique of bootstrap resampling without replacement to match statistically identical participant students with comparison groups of students. Without replacement is a method that eliminates individuals available for analysis. Students that could not be matched within the constrained caliper width were not used in the study. A standardized caliper width of .05 was be used for this analysis and was intended to account for potential bias (Soria et al., 2017). An optimal fixed caliper width of .05 was used to match enough students for statistical significance, while managing potential conflicts of self-selection bias. Nevertheless, the available sample of students analyzed was reduced due to the limited caliper width and contributed to student data unavailable for analysis.

Threats to Internal Validity

Limitations to the estimated impacts from participating in SL courses on students' term-to-term persistence could have been influenced by selection bias as participating students who attended classes were likely different from students who chose not to attend. These differences may have also been associated with student persistence. For example, males may be more likely to attend athletic events and more likely to persist; being male would be associated with both the treatment or activity (athletic events) and the student outcome (persistence). This is a unidimensional example; however, predicted propensity scores used in this study accounted for a large number of individual covariates and matched individuals with similar scores to reduce self-selection bias and possible limitations inherent within the employed research methods.

CHAPTER IV

RESULTS

This study examines the impacts of a SL curriculum on term-to-term persistence of students who attend SL courses. More specifically, the persistence of students who attend either lower- or upper-division courses was explored along with various subgroup populations (hereafter referred to as "participant" or "participating" students). Using a historical dataset from USU and an analytical approach combining complex multivariate logistical regression techniques through prediction-based propensity score matching (PPSM), this study seeks to answer an underlying research question: What are the influences of a SL curriculum on student persistence to the next term?

This chapter provides detailed results for the analyses performed in this study. The chapter will present descriptive statistics and a synopsis of the analytical procedure. Estimation results from the statistical analyses guided by three research questions are then provided.

Descriptive Statistics of Analyzed Students

The analyzed dataset from USU during the years of 2016, 2017, and 2018 were selected from an undergraduate population of students. Descriptive statistics and significant empirical analysis results from selected subgroups can be generalized to the respective population of students. Table 5 displays the populations of participating and control groups of students that were available for analysis.

The statistical analyses used in this study investigated the impacts of term-to-term persistence on groups of students who participated in 254 SL courses across six terms. The analysis paired 8,948 participating students with similar groups of students who chose not to take SL courses.

Table 5

Students Matched for Analysis and Courses by Term

n	Student group	Term	Lower courses	Upper courses	All courses
1,092	Participating group of students	Sp. 16	4	24	28
9,405	Control group of students	Sp. 16	-	-	
963	Participating group of students	Fa. 16	3	20	23
10,078	Control group of students	Fa. 16	-	-	
1,588	Participating group of students	Sp. 17	11	36	47
8,821	Control group of students	Sp. 17	-	-	
1,564	Participating group of students	Fa. 17	3	34	37
10,112	Control group of students	Fa. 17	-	-	
2,030	Participating group of students	Sp. 18	14	48	62
8,689	Control group of students	Sp. 18	-	-	
1,697	Participating group of students	Fa. 18	7	50	57
10,101	Control group of students	Fa. 18	-	-	
8,948	Participating group of students	6-Terms	42	212	254
57,206	Control group of students	6-Terms	-	-	

Answering research questions H_2 and H_3 required students to be categorically separated using their enrollment in either a lower- or upper-division course. There was a total of 42 lower-division and 212 upper-division courses with enrolled students available and matched for analysis across 6 terms and 3 years. Across the whole study, a comparison group of 57,206 undergraduate control students were matched with statistically identical participant students.

As illustrated in Table 6, analyzed student subgroups differ from university three-year averages. In regard to course modalities, a notable difference of 35% of the analyzed participant students were enrolled in SL Blended (see Appendix A) courses compared to only 5% of all other university students who were enrolled in Blended courses, whereas the opposite for online course offerings illustrated that only 4% of the students analyzed took SL online courses, although the institutional average was 33% of students taking online courses during the research timeframe.

Table 6

Students Matched for Analysis Demographics

Demographic subgroup	*n*	Analyzed participants %	USU 3 yr avg %
Face to face and broadcast	5,491	61	81
Blended	3,090	35	5
Online	364	4	33
Full-time students	7,949	89	66
Part-time students	982	11	34
First time in college	4,905	55	18
Female	5,030	56	47
Male	3,915	44	53
Hispanic or Latino	276	3	6
Two or more	229	3	2
Other unspecified	223	2	4
Asian	157	2	1
Black or African American	108	1	1
Pacific Islander	25	0.28	0.35
American Indian/Alaskan Native	40	0.45	2
White/Caucasian	8,149	91	82

The analyzed student demographic data shows a larger proportion of full-time students (89%) took SL courses than their university counterparts at 66%, whereas there was a substantially lower (11%) of part-time SL participants when compared to the (34%) USU average. Most all other student demographics of analyzed SL participants reflect the institutional average with exception of students in the subcategory of First Time in College (see Appendix A for definition). During the 3-year timeframe of this study, 55% of the SL participants were categorized as First Time in College, which is much higher than the comparable 18% institutional average.

Analytical Procedure

The primary analyses for this study were carried out using a quasi-experimental design using a statistical process that included PPSM. The statistical process included bootstrap resampling iterations to estimate statistical significance and unstandardized effect size outcome measures to answer each of the proposed research questions. Practical, or unstandardized, effect size measures were used in this study to interpret the contextual comparisons of mean differences of student persistence outcomes (Baguley, 2009; Cohen, Cohen, Aiken, & West, 1999; Wilkinson, 1999). The unstandardized effect size measures represent an estimated number of students who persisted to the next term along with respective amounts of retained tuition dollars.

Estimated outcome results in this chapter are presented using figures developed from data tables found in Appendices D, E, and F. Each persistence outcome figure illustrates a percentage of difference in persistence outcomes on the x-axis. Significant results associated with the outcomes are categorized using an asterisk as * $p < .05$, ** $p < .01$ or *** $p < .001$. All confidence intervals were calculated using a 95% probability value that represents the analyzed population parameters. A graphical representation of significant results for each categorized outcome can be identified when the outcome percentage and corresponding confidence interval values do not pass through zero on the x-axis. To illustrate unstandardized effect sizes, each row contains the sample *n* value of analyzed student participants and a corresponding average number of impacted students, based on the reported outcome percentage along with its confidence intervals. The number of students impacted by the outcomes was selected as a practical and interpretable unstandardized effect size metric.

First, to answer the research question regarding overall impacts of persistence on students who participate in SL courses (Hypothesis 1) and outcome differences between upper and lower-division courses (Hypothesis 2), all student subgroups and terms were combined using the PPSM methods. Second, to further investigate more granular results, outcomes were categorized by term and by combining lower- and upper-course division students, lower-course division students, and upper-course division students. Last, using PPSM to estimate influences on student subgroups (Hypothesis 3), each population was categorically and independently analyzed using the following nine populations: (1) combined upper- and lower-division courses, (2) lower-division courses, (3) upper-division courses, (4) Spring term of 2016, (5) Fall term of 2016, (6) Spring term of 2017, (7) Fall term of 2017, (8) Spring term of 2018, and (9) Fall term of 2018.

The following sections will expound on each research question and its corresponding hypothesis. The sections will include descriptive statistics and analyzed group matching details, along with detailed results and statistically significant insights.

Prediction-Based Propensity Score Matching Results

Hypothesis I (H_1): Difference in Difference Effects of Participation in SL Activities

The first hypothesis addressed the following research question: Does participation in the curricular high impact practice (HIP) of SL have a significantly positive difference in the means on students' likelihood to persist to the next term? Based on prior seminal research and generalizable results (Kuh, 2013), it was hypothesized that a course using a SL HIP curriculum would produce positive outcomes of persistence on participating students.

The null hypothesis of (H_1) states: There were no positive differential effects on persistence to the next term for student participants of SL activities at USU. The PPSM results of this study concluded an overall positive difference in persistence outcomes for participating groups of students when compared to their counterparts, thereby rejecting the stated null hypothesis of H_1 and significant (*p* = 0.0009).

Descriptive statistics for H_1. Table 7 displays a summary of overall significant results and descriptive statistics of students matched for analysis. There were 8,959 participating students enrolled in 254 courses available for the overall analysis. After 30 bootstrap resampling iterations without replacement, 99.9% of the participating students were successfully matched on their similarity prediction and propensity scores with the available 57,206 control group of students. When student groups from all available terms and course divisions were collectively analyzed using PPSM, there was a positive 1.34% impact of persistence on the 8,948 students that participated in SL courses. The average number of retained students was 120 over the analyzed academic timeframe of 3 years/6 terms.

Table 7

Executive Summary for Question 1

Characteristics	Summary statistics
Overall difference in persistence	1.34%, CI% [.54, 2.14]
Overall student retention	120, CI [48, 191]
Participating student groups	8,959
Control student groups	57,206
Students matched for analysis	8,948
Students similarity after matching for analysis	99%
Students similarity after matching by propensity scores	99%
Students similarity after matching by prediction scores	99%
Percent Female	56%
Percent White	91%
Percent Hispanic/Latino	3%
Terms available for analysis	Sp16, Fa16, Sp17, Fa17, Sp18, Fa18

Note. Overall results have a $p = 0.0009$ with a 95% confidence interval.

As referenced in Table 7, the population of analyzed students during the 3 years of analysis illustrates 56% of female student participants in SL courses which is 6 percentage points higher than the university average during that timeframe. There were only 44% of male student participants which is nine percentage points lower than attended the university during the analyzed timeframe. While the USU student body was predominantly White (82%) during this study's timeframe, 91% of all participant student were of that ethnicity. Whereas, 6% of the student population was Hispanic/Latino during the timeframe and only 3% of the participant students were of that ethnic group.

When using the PPSM methods, each student eligible for analysis was assigned a prediction score prior to matching. As illustrated in Figure 12, 87% of the lower-division groups of students were found to be similar based on their assigned prediction scores. After 30 iterations of bootstrap resampling and constrained by a .05 caliper width and without replacement, 99% of the participant and control groups were matched on their prediction score similarities and made available for analysis.

Each student eligible for analysis was also assigned a propensity score prior to matching. As illustrated in Figure 13, 80% of the lower-division groups of students were found to be similar

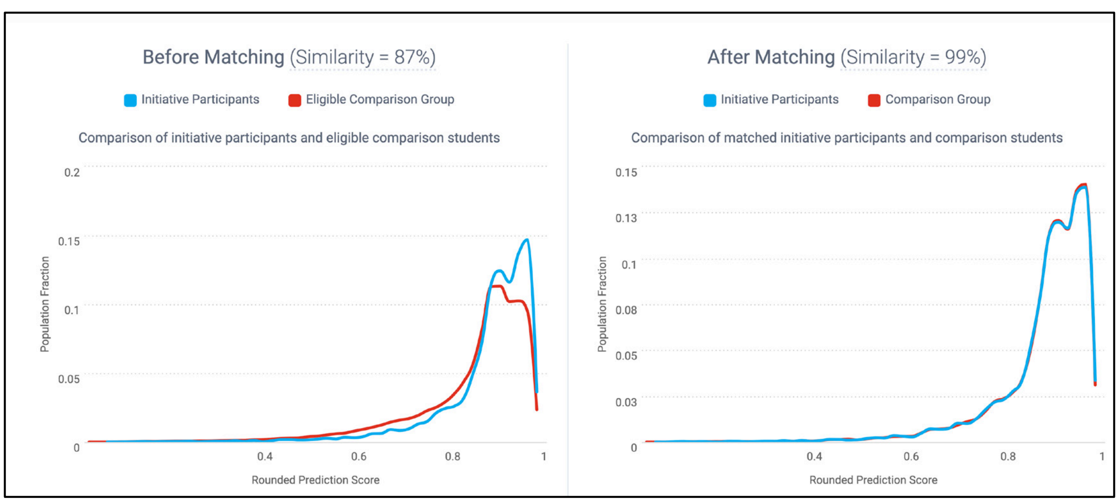

Figure 12. Combined lower and upper division prediction score matching results.

based on their assigned prediction scores. After 30 iterations of bootstrap resampling and constrained by a .05 caliper width and without replacement, 99% of the participant and control groups of students were matched on their propensity score similarities and made available for analysis (see Figure 13).

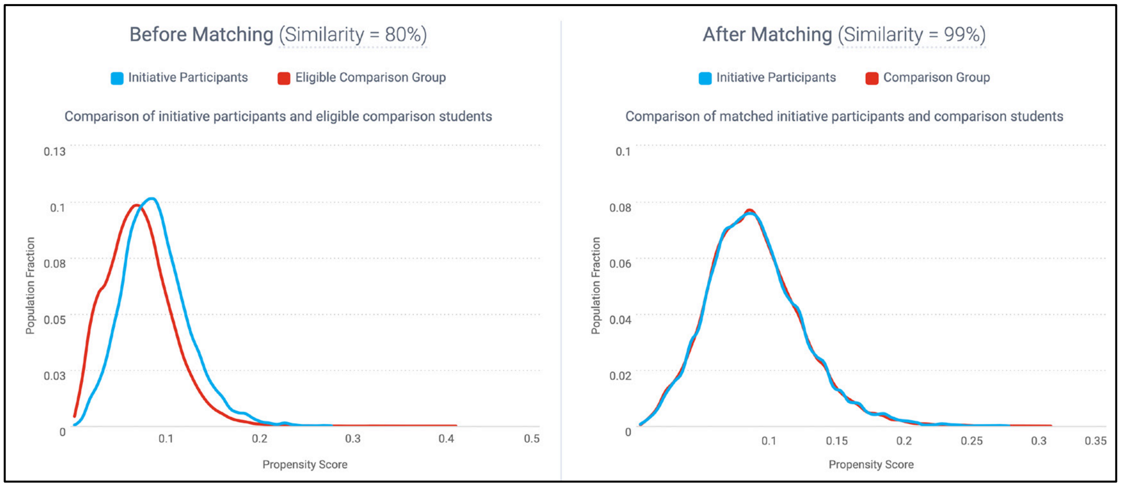

Figure 13. Combined lower and upper division propensity score matching results.

Detailed results for research question 1. After following Astin and Antonio's (2012) Input, Environment, Output (IEO) model to structure the research methodology and employing statistical methods to both account for potential bias and isolate SL as the independent treatment variable, a combination of analyzed groups of students from both upper- and lower-division courses concluded an overall positive dependent variable of persistence.

The overall analysis of this question validates prior seminal research and generalizable results hypothesizing student participation in SL courses will experience positive outcomes of term-to-term persistence. This study's analysis of combined participating student groups from both lower- and upper-division courses report a positive 1.34% difference of persistence calculated over 3 years/6 terms (see Table 7). Of the 8,948 participating students available for analysis, an average of 120 students were retained over the timeframe of the study. Using a 95% confidence interval, there was a possible range of retained students that contained the value of the analyzed population. The lower and upper bounds of the range fell between 48 and 191 students and were significant ($p = 0.0009$).

Difference in difference: All terms. Positive results of 1.34% for the combined groups of students were analyzed as an aggregate of all terms and subgroups. The executive summary Table 7 reports that 99.9% of participant and control students were matched based on predicted criterion outcomes. The derived counterfactual of 0.8858 found in Table D1, and visually represented in Figure 14, provided a comparative value used to determine if the predictive model introduced bias in the analysis. By using the observed 0.9033 outcome result for the comparison group found in Table D1, the study determined there was less than a 3-percentage point difference of actual persistence from the derived counterfactual value of 0.8858, thus validating an effective predictive model.

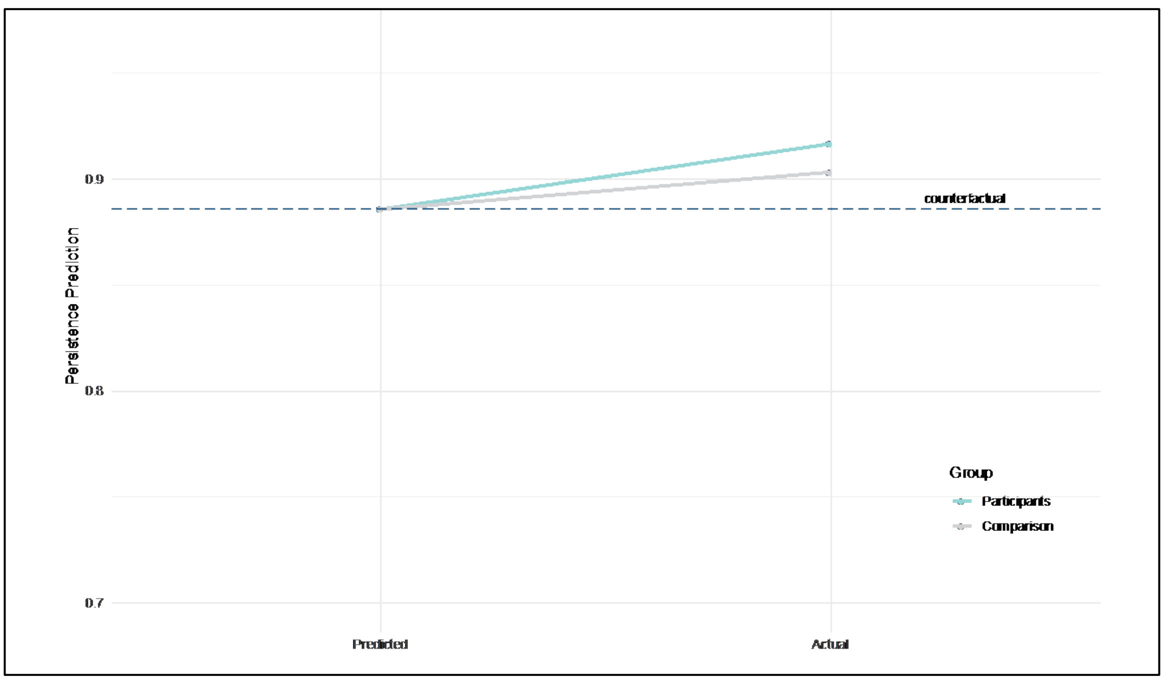

Figure 14. Derived counterfactual and comparison results for combined lower and upper divisions.

The 8,948 participating students from both lower- and upper-division courses were segregated by terms and independently analyzed to determine the difference of persistence between the two groups (see Figure 15). Using analyzed results found in Table D1, Figure 16 was developed to represent statistical significance and unstandardized effect sizes of students retained for each term with a 95% confidence interval and respective ranges. Significant terms can be visually identified when the range of the analyzed population does not pass through 0 on the x-axis.

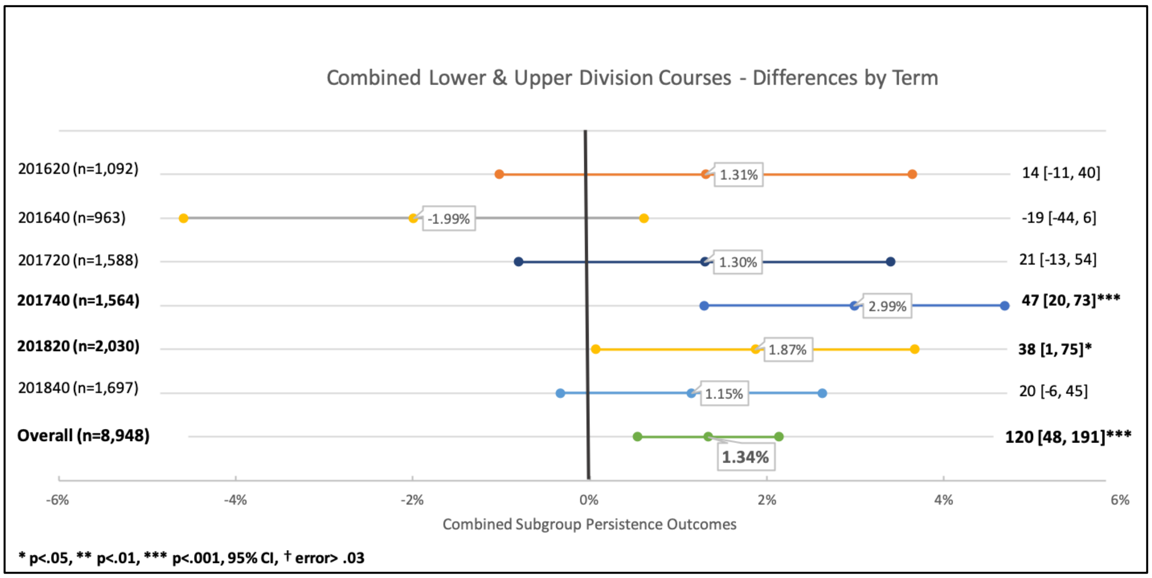

Figure 15. Combined lower and upper division term-based difference in difference outcomes.

Overall effects of the treatment on the 8,948 participating students show a positive and significant impact of 1.34% with an average effect on 120 retained students over the timeframe of the study. Of the six independently analyzed terms, only Fall of 2017 (201740) and Spring of 2018 (201820) returned significant differences between the analyzed groups of students. Participating students in each of these terms presented a higher percentage of impact than all analyzed terms combined.

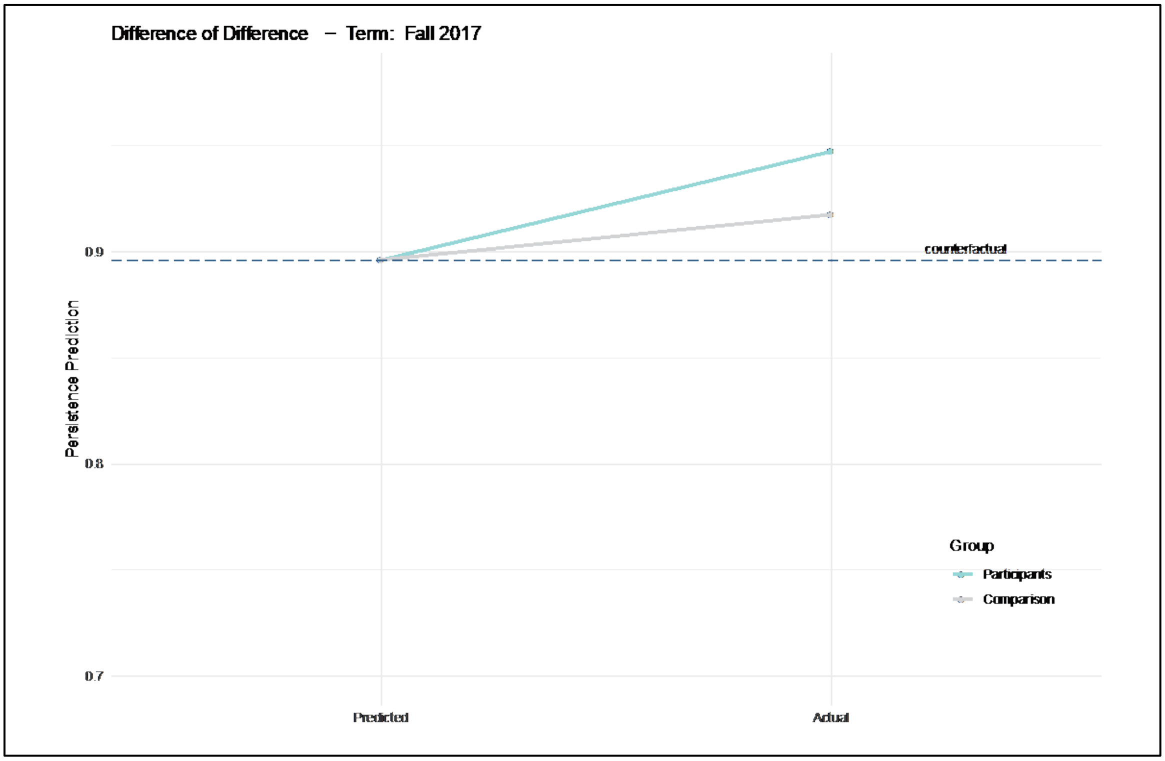

Figure 16. Derived counterfactual and comparison results for Fall 2017 combined lower and upper divisions.

As the PPSM methods require populations greater than 250 (Kil, Chan, et al., 2017), there were more than enough matched students to provide confidence for accurate results for each of the independently analyzed terms.

Difference in difference: Fall 2017. Analysis of Fall of 2017 calculated a derived counterfactual of 0.8962, (see Table D1), provided a comparative value used to determine if the predictive model introduced bias in the analysis. In addition, using the observed 0.9176 outcome results for the comparison group (see Table D1), there was less than a 3-percentage point difference of actual persistence from the derived counterfactual value of 0.8962, validating an effective predictive model for that term-based analysis.

In the Fall of 2017, data from 1,564 analyzed participants produced a significant (p = 0.0006) and positive 2.99% impact when compared to their counterparts. This equated to 47 participant students persisting to the next term (Spring 2018). The confidence interval around the observed difference ranges between 20 students on the lower boundary to 73 at the upper end. A conservative view of these results leads me to expect at least a 1.29% impact, which is only 0.05% lower than the average change in persistence of the overall group.

Difference in difference: Spring 2018. Analysis of Spring 2018 calculated a derived counterfactual of 0.8704, see Table D1 and Figure 17 provided a comparative value used to determine if the predictive model introduced bias in the analysis. When using the observed 0.8843 outcome results for the comparison group (see Table D1), there was less than a 3-percentage point difference of actual persistence from the derived counterfactual value of 0.8843, validating an effective predictive model for that term-based analysis.

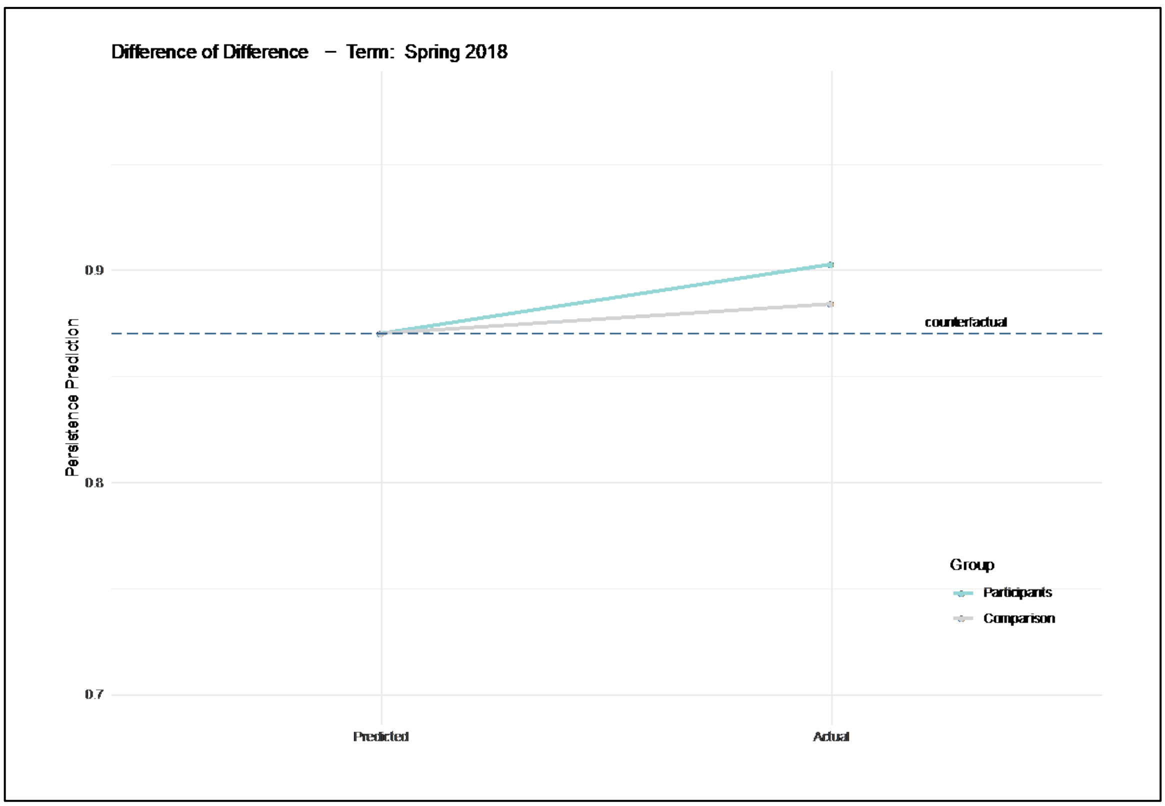

Figure 17. Derived counterfactual and comparison results for Spring 2018 combined lower and upper divisions.

More participants were analyzed in Spring 2018 (2,030) than Fall 2017 (1,564) and demonstrated a significant ($p = 0.0415$) and positive 1.87% impact. This equated to 38 participant students persisting to the next term–only 9 less students than the prior term. However, when viewing the number of students affected by using the confidence interval range illustrated a range between 1 and 75 students. Once again, taking a conservative view of the Spring 2018 results leads me to expect only a 0.07% positive impact on participating students who would persist to the next term, much lower than the 1.29% lower interval boundary of Fall 2017.

Difference in difference: Remaining terms. Analysis of the remaining 6 terms (Spring 2016 [201620], Fall 2016 [201640], Spring 2017 [201720], and Fall 2018 [201840]) did not return significant ($p < 0.05$) results and did not provide sufficient evidence to accept or reject the stated null hypothesis H_1 within the parameters of this study. Consequently, the analyzed results for participating students enrolled during those terms were not interpreted from this analysis.

Hypothesis II (H_2) Difference in Difference Effects of Lower- and Upper-Division Student Participations in SL Activities

The second hypothesis addressed the following research question: Is there a significant difference in the student persistence mean values based on SL course levels (e.g., lower-division or upper-division)? Alexander Astin (1970, 1985) spent his career analyzing higher education and programming. He recommended differentiating sampling groups by freshmen/sophomore (lower division) and junior/senior (upper division) for greater accuracy. To respectively measure the difference in difference effects for each division, student data was separated and independently analyzed by grouping 1000 and 2000-level course participants, and 3000 & 4000-level course participants.

The null hypothesis of (H_2) states: There were no differential effects on term-to-term persistence between groups of upper- and lower-division student participants of SL activities at

USU. This study's PPSM results concluded an overall positive difference in persistence outcomes for lower-division student participants that were significant (*p* = 0.0019). Whereas, analysis of upper-division student participants' results was inconclusive and insignificant (*p* = 0.50).

Further analysis of the upper-division results exposed potential problems with predictive modeling used to match this group of students and will be illustrated later in this chapter with a detailed discussion in Chapter V. Consequently, the results for the upper-division groups of students does not provide conclusive evidence that can be used to compare differences between lower- and upper-division students. Thus, the PPSM methods of analysis results are insufficient to either reject or accept the stated null hypothesis of H_2.

Descriptive statistics for H_2. Table 8 displays a summary of overall significant results and descriptive statistics of students matched for analysis for both lower- and upper-division courses. There were 3,331 participating students enrolled in 42 lower-division courses available

Table 8

Executive Summary for Question 2

Participating student characteristics	Lower division	Upper division
Overall change in persistence	2.61%, CI% [.97, 4.25]	0.08%, CI% [-.75, .91]
Overall student retention	86, CI [32,140]	4, CI [-38,46]
p value	0.0019	0.8575
Control student groups	37,034	20,172
Participating student groups	3,331	5,924
Students matched for analysis	3,290	5,024
Students matched for analysis	98.7%	84.8%
Students matched by propensity scores	97%	96%
Students matched by prediction scores	98%	97%
Percent Female	55%	55%
Percent White	90%	92%
Percent Hispanic/Latino	2%	4%
Terms available for analysis	Sp16, Fa16, Sp17, Fa17, Sp18, Fa18	

Note. 95% CI.

for the overall analysis. After 30 bootstrap resampling iterations without replacement, 98.7% (3,290) of the participating students were successfully matched on their similarity prediction and propensity scores with the available 37,034 control group of lower-division students. When student groups from all available terms and the lower-division courses were collectively analyzed using PPSM, there was a positive 2.61% impact of persistence on the participating students. The average number of retained students was 86 over the analyzed academic timeframe of 3-years/6-terms.

There were 5,924 participating students available for analysis in 212 upper-division courses. After 30 bootstrap resampling iterations without replacement, 84.8% of the participating students were successfully matched on their similarity prediction and propensity scores with the available 20,172 control group of upper-division students. When student groups from all available terms and the upper-division courses were collectively analyzed using PPSM, there were insignificant (p = 0.50) results from analyzed participating students. The insignificant results provide no evidence of retained upper-division students over the analyzed academic timeframe of 3 years/6 terms.

Over the 3 years, 55% of the analyzed lower-division student participants were female, five percentage points higher than the university average during that timeframe (see Table 8). Whereas, the 45% of male student participants is eight percentage points fewer than those attending the university during the analyzed timeframe. Lower-division student participants were represented as 90% of White ethnic descent, eight percentage points higher than the university. However, only 2% of the lower-division participants represented the Hispanic/Latino ethnic group, compared to 6% of the USU student body.

Like the participants in lower-division courses, participants in upper-division courses were 55% Female. Upper-division student participants had a slightly higher ethnic representations with 92% White and 4% were of Hispanic/Latino descent.

Lower division matching. To use PPSM methods, each student eligible for analysis was assigned a derived prediction score prior to matching. As illustrated in Figure 18, 88% of the lower-division students were found to be similar based on their assigned prediction scores. After 30 iterations of bootstrap resampling constrained by a .05 caliper width and without replacement, 98% of the participant and control groups of students were matched on their prediction score similarities and made available for analysis.

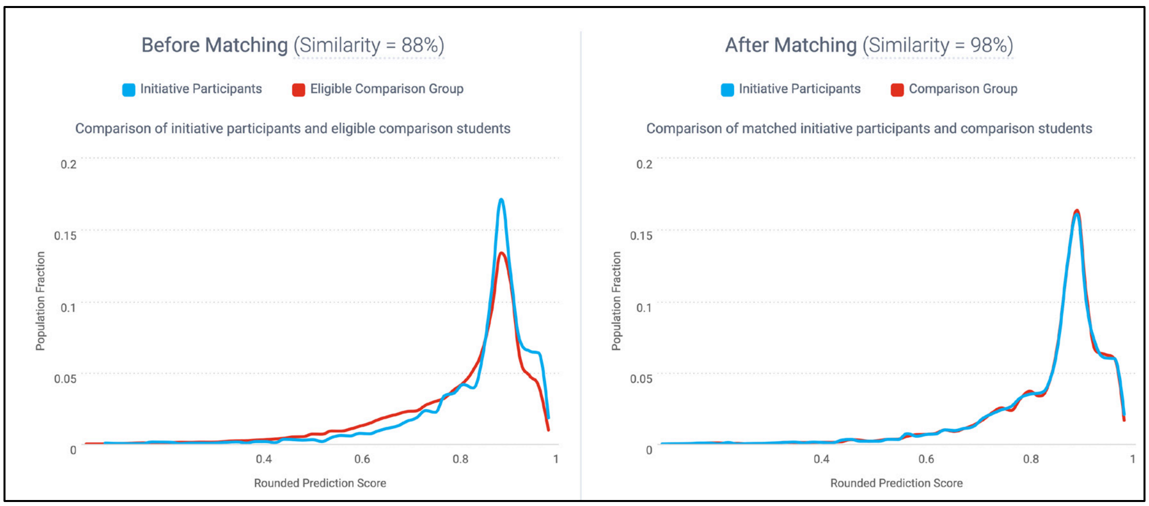

Figure 18. Lower division prediction score matching results.

Each eligible student for analysis was also assigned a derived propensity score prior to matching. As illustrated in Figure 19, 72% of the lower-division students were found to be similar based on their propensity scores. After 30 iterations of bootstrap resampling constrained by a .05 caliper width and without replacement, 97% of the participant and control students were matched on their propensity score similarities and made available for analysis.

Upper division matching. Each upper-division student eligible for analysis was assigned a prediction score prior to matching. As illustrated in Figure 20, 83% of the upper-division groups of students were found to be similar based on their assigned prediction scores. After 30 iterations of bootstrap resampling constrained by a .05 caliper width and without replacement, 97% of the

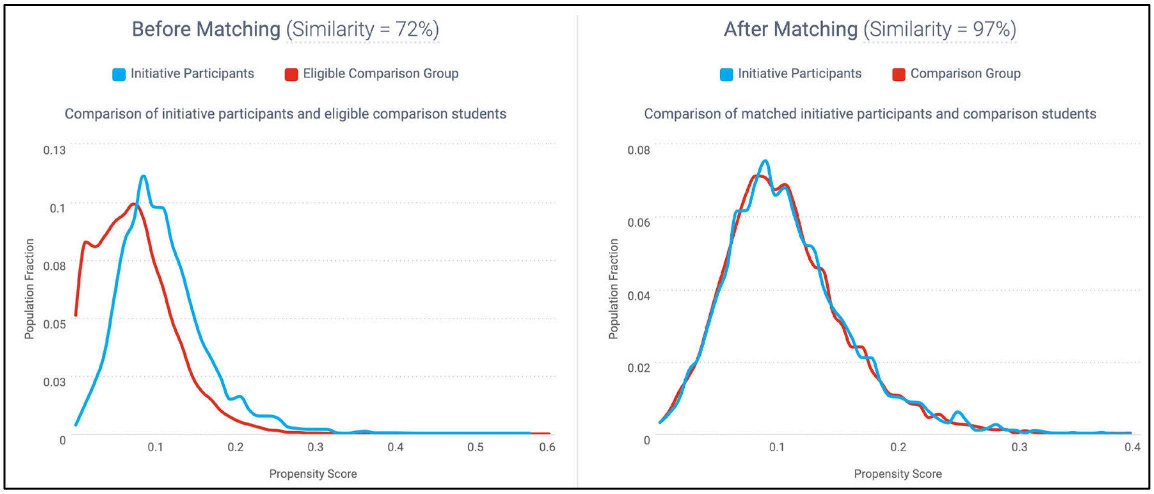

Figure 19. Lower division propensity score matching results.

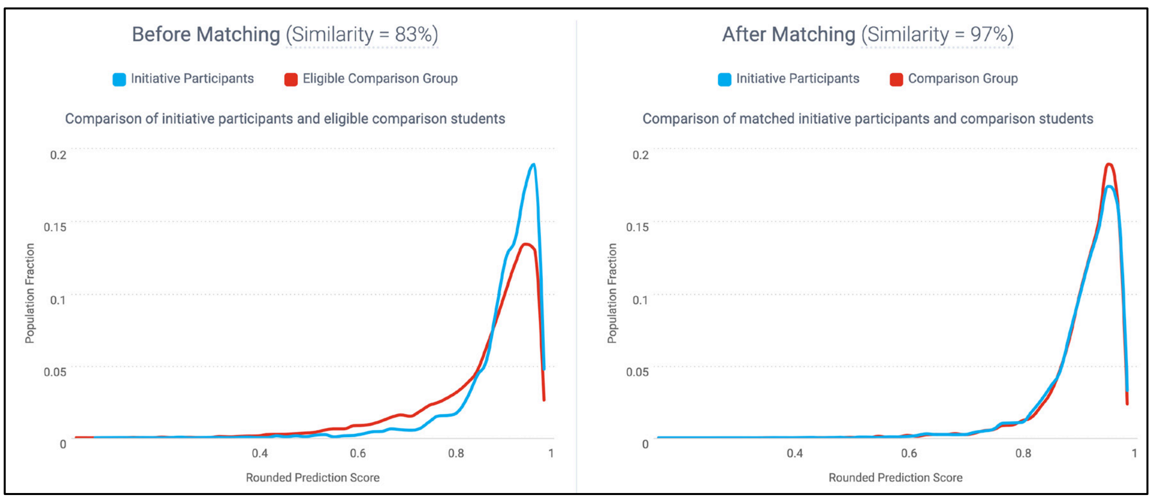

Figure 20. Upper division prediction scores matching results.

participant and control groups of students were matched on their prediction score similarities and made available for analysis.

Each upper student eligible for analysis was also assigned a propensity score prior to matching. As illustrated in Figure 21, 65% of the upper-division groups of students were found to be similar based on their assigned propensity scores. After 30 iterations of bootstrap resampling and constrained by a .05 caliper width and without replacement, 96% of the participant and

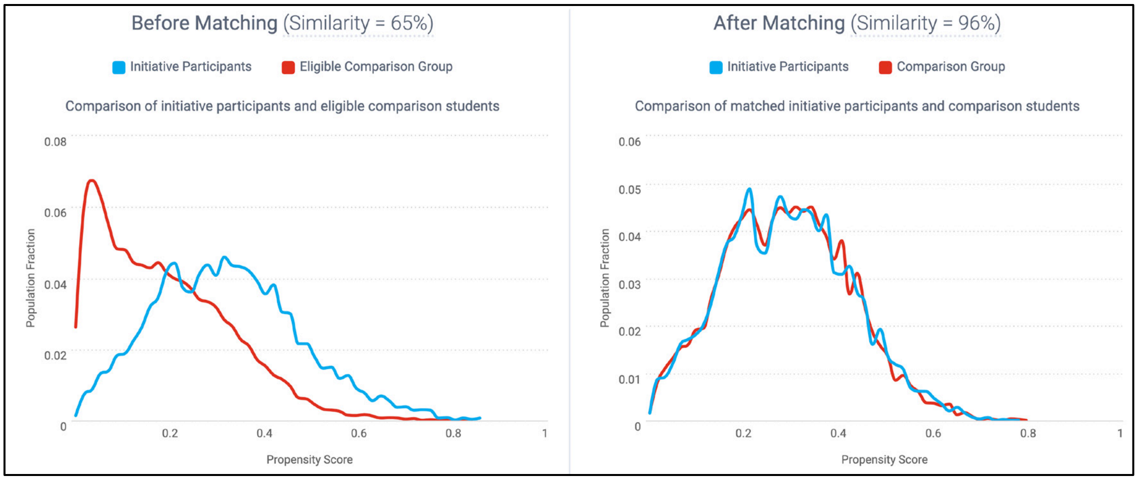

Figure 21. Upper division propensity scores matching results.

control groups of students were matched on their propensity score similarities and made available for analysis.

Detailed results for research question 2. Research question 2 was designed to investigate persistence impact differences between lower- and upper-division students. As such, student data eligible for analysis was segregated into two respective groups and analyzed independently. After employing PPSM methods on each division while aggregating all 6 terms, the overall results concluded a significant and positive 2.61% impact was experienced by lower-division student participants, where 86 students were retained. Whereas, the overall results for upper-division students provide no significance or evidence of impact on persistence.

Lower division details. Using results from question 1, where combined groups of students from both lower- and upper-division courses was aggregated for analysis, as a relative baseline (see Figure 22) a 1.34% difference of persistence had a much smaller impact than the 2.61% realized by lower-division participating students. Effects of the treatment on the 3,290 lower-division student participants available for analysis show an average of 86 students were retained over the timeframe of the study. Using a 95% confidence interval, the possible range of retained students fell between 32 and 140 students at a significance level of $p = 0.0019$.

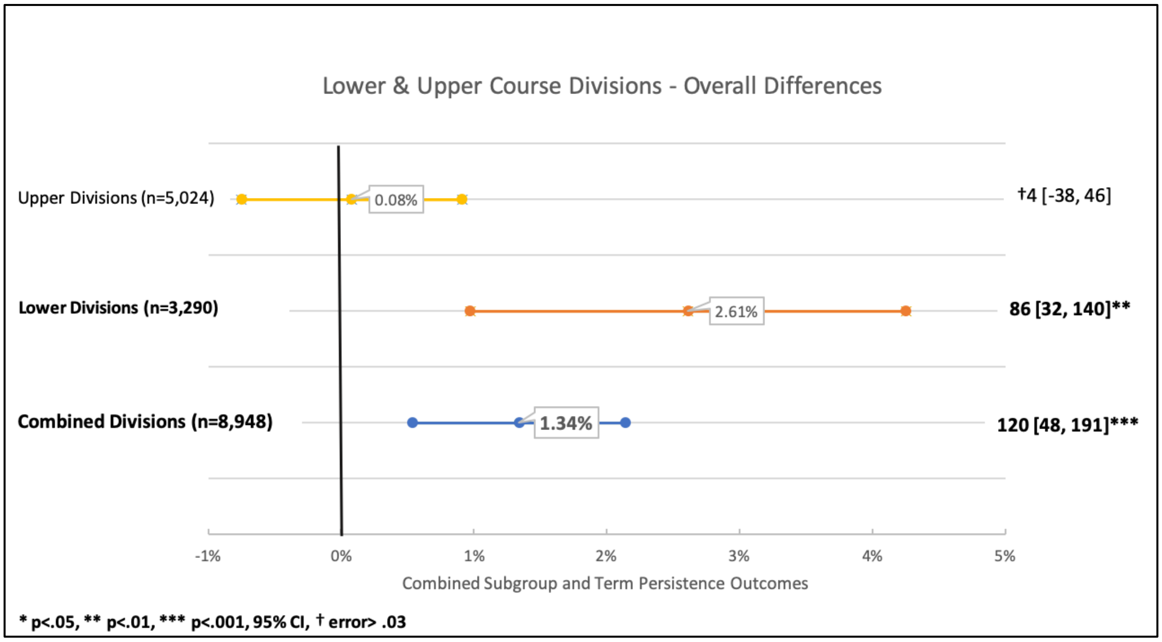

Figure 22. Lower and upper division overall results.

Difference in difference: All terms. Positive results of 2.61% for the lower-division students were analyzed as an aggregate of all terms and subgroups. The executive summary table (Table 8) reports that 98.7% of lower-division participant and control students were matched based on predicted criterion outcomes. The derived counterfactual of 0.8501, see Table E1 and Figure 23, provided a comparative value that was used to determine if the predictive model introduced bias into the analysis. Using the observed 0.8362 outcome results for the comparison group (see Table E1), there was less than a 3-percentage point difference of actual persistence from the derived counterfactual value of 0.8501, validating an effective predictive model.

The 3,290 participating students in lower-division courses were segregated by terms and independently analyzed to determine difference of persistence between the two groups of students (see Figure 22). Using analyzed results found in Table E1, Figure 24 was developed to represent statistical significance and unstandardized effect sizes of students retained each term.

Overall effects of the treatment on the 3,290 participating students available for analysis

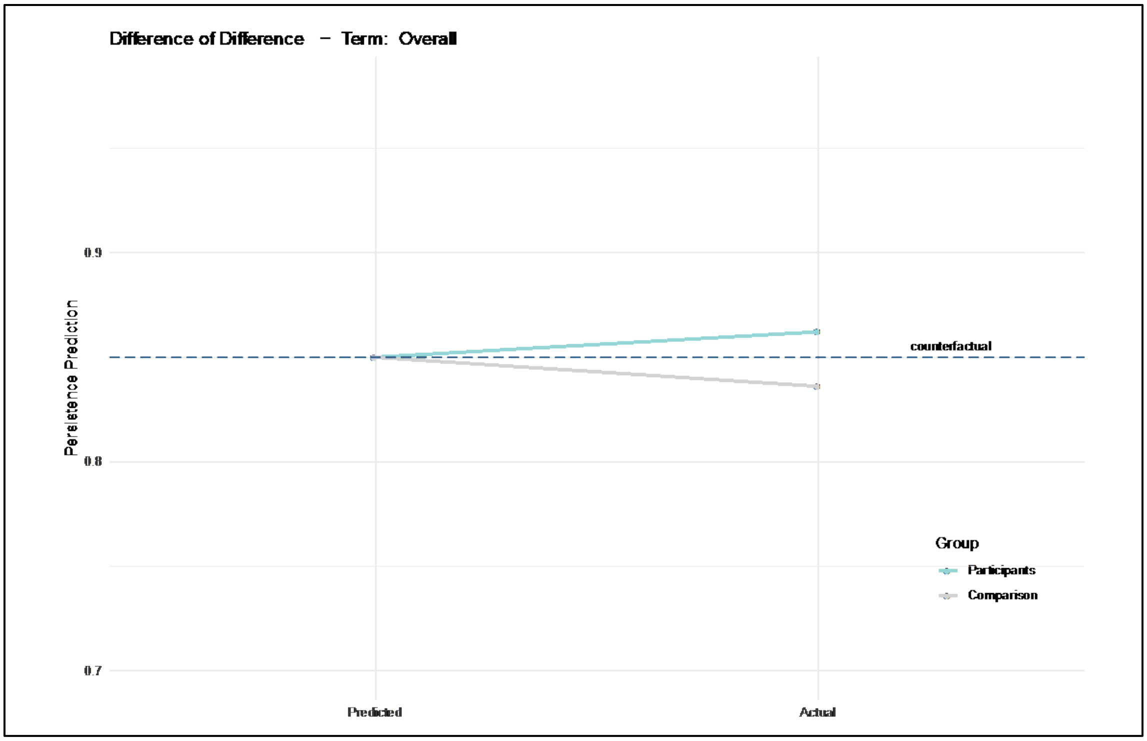

Figure 23. Derived counterfactual and comparison results for all terms in lower division.

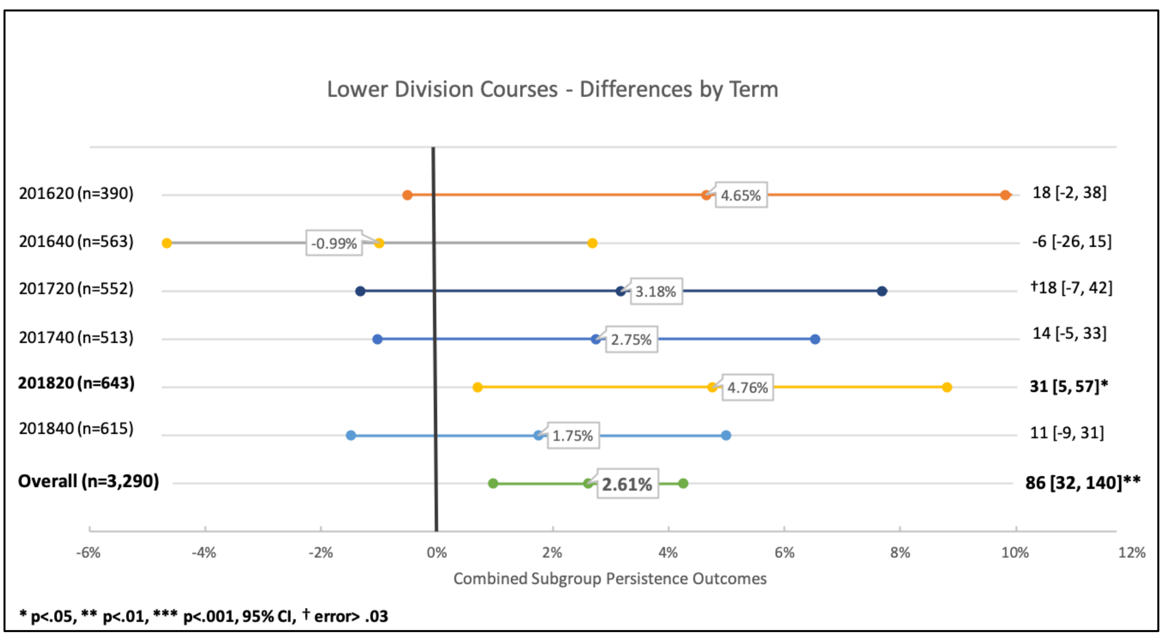

Figure 24. Lower division term-based difference in difference outcomes.

show a positive and significant impact of 2.61%, equating to a positive effect on an average of 86 retained students over the timeframe of the study. Of the 6 independently analyzed terms, only the Spring of 2018 (201820) returned significant results where 643 participant students were analyzed. Nevertheless, for each of the independently analyzed terms, there were a sufficient number of participant and eligible control students to provide adequate statistical power and accurate results. However, analysis of Spring 2017 (201720) for lower-division courses failed the predictive model test with a 3.39% of error from the counterfactual.

Difference in difference: Spring 2018. Participating students in the Spring of 2018 realized a 4.76% positive impact, 2.15% higher than the overall analysis of all terms combined for lower-division students. Analysis of the Spring 2018 data provides a derived counterfactual of 0.8158 (see Table E1 and Figure 25). The observed 0.7920 outcome results for the comparison group was less than a 3-percentage point difference of actual persistence from the derived counterfactual value of 0.8158, thus validating an effective predictive model for that term-based

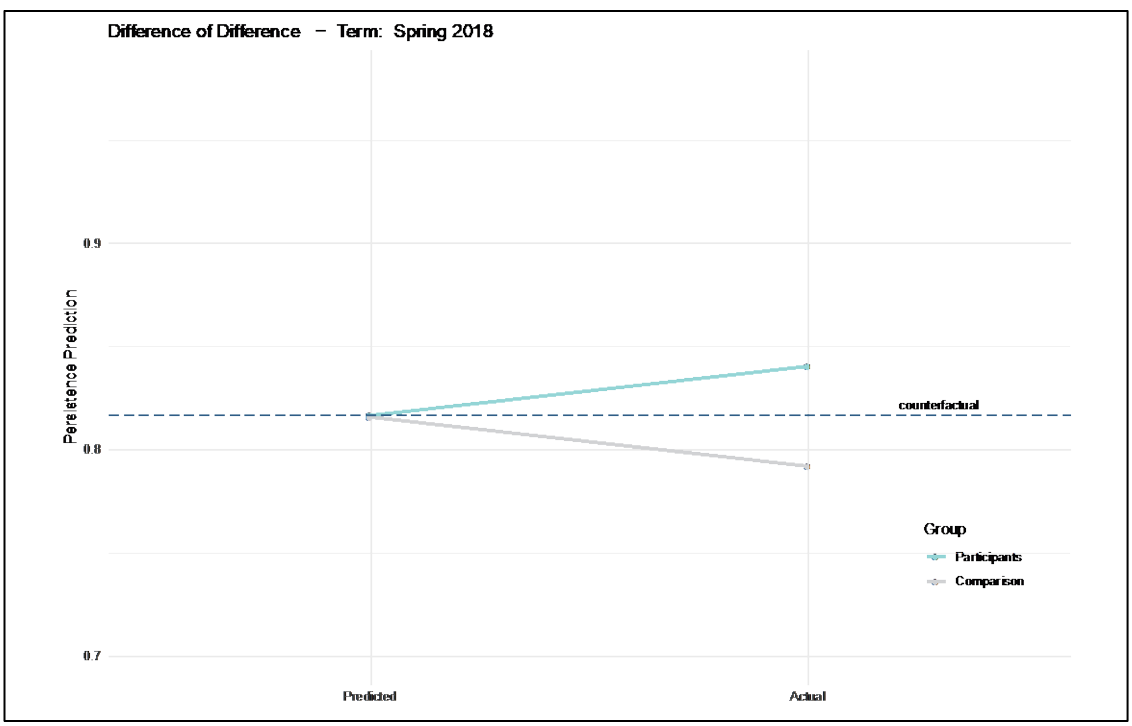

*Figure 25*1. Derived counterfactual and comparison results for Spring 2018: Lower division.

analysis (see Table E1). In the Spring of 2018, data was analyzed from 643 participants that produced a significant ($p = 0.0213$) and positive 4.76% impact when compared to their counterparts, equating to 31 retained students persisting to the next term. A relatively large confidence interval around the observed differences ranges between 5 students on the lower boundary to 57 at the upper end. While a conservative view of these results leads me to expect at least a 0.71% impact, which is only 0.26% lower than the average change in persistence of the overall group.

Analysis of lower-division students from the remaining 5 terms (Spring 2016 [201620], Fall 2016 [201640], Spring 2017 [201720], Fall 2017 [201740], and Fall 2018 [201840]) did not return significant ($p < 0.05$) results and, consequently, did not provide sufficient evidence to accept or reject the stated null hypothesis H_2. Additionally, results for Spring 2017 (201720) failed both significance testing and predictive model testing and, consequently, there were not any attempts to interpret results for that term.

Upper division details. Analysis of upper-division students' data from all terms and subgroups aggregated produced insignificant results. The executive summary table (Table 8) reports that 85% of upper-division participant and control students were matched based on predicted criterion outcomes. A derived counterfactual of 0.9170 (see Table E2 and Figure 26), provided a comparative value used to test if predictive model introduced bias into the analysis. Using the observed 0.9510 outcome results for the comparison group (see Table E2), a 3.40% error between the counterfactual and the actual comparison group outcome values was discovered. An error greater than $\pm$ 3% signifies a threat to the predictive model's validity. Analysis of the upper-division groups of students resulted in a 3.40% error and therefore, failed the predictive model test. Thus, upper-division groups of students and combined term results were not considered valid and were not interpreted for this study.

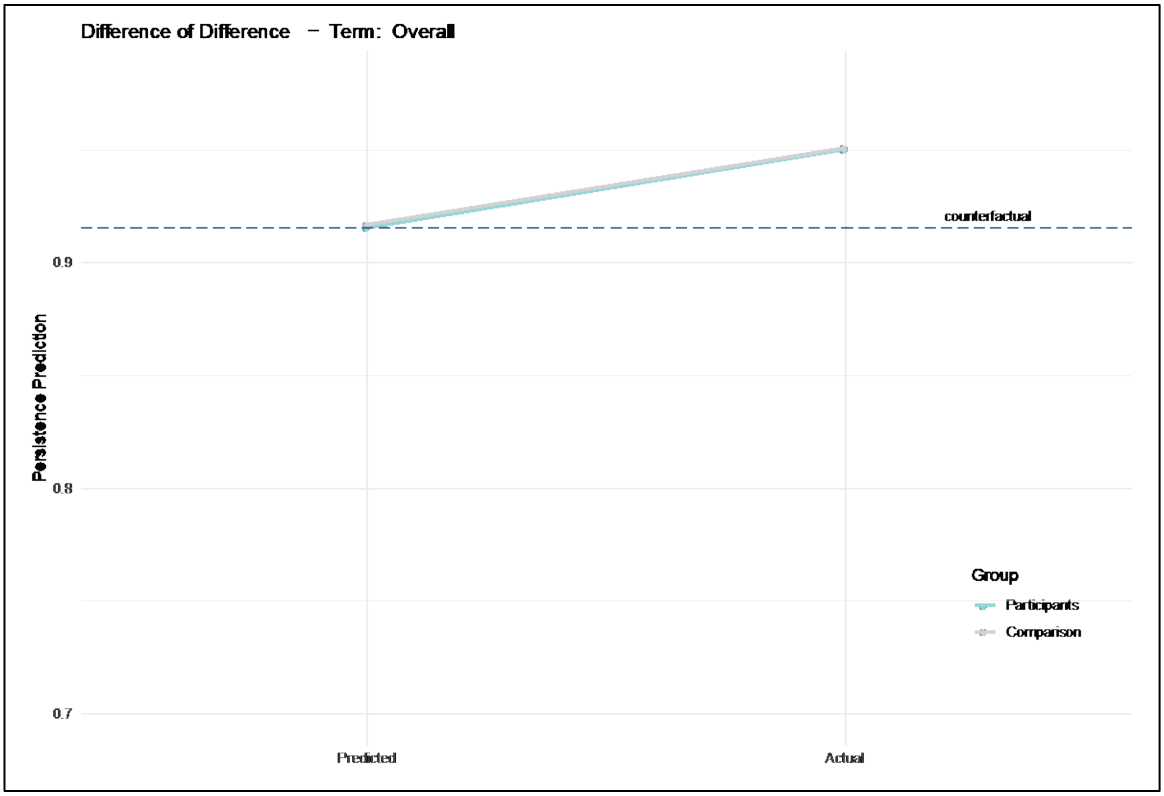

Figure 26. Derived counterfactual and comparison results for all terms in upper division.

Analysis of five of the six upper-division terms (Spring 2016 [201620], Spring 2017 [201720], Fall 2017 [201740], Spring 2018 [201820], and Fall [201840]) failed to produce both significant ($p < 0.05$) and predictive model testing with errors $< \pm 0.03$. However, in the Fall of 2016 (201640), there were 500 participant students, which is adequate for statistical power (see Figure 27). The analysis passed a predictive model test, error $< \pm .03$, but it failed to show statistical significance, ($p = 0.1746$). Consequently, there was insufficient evidence found from analysis of the participants in upper-division courses to either accept or reject the stated null hypothesis H_2.

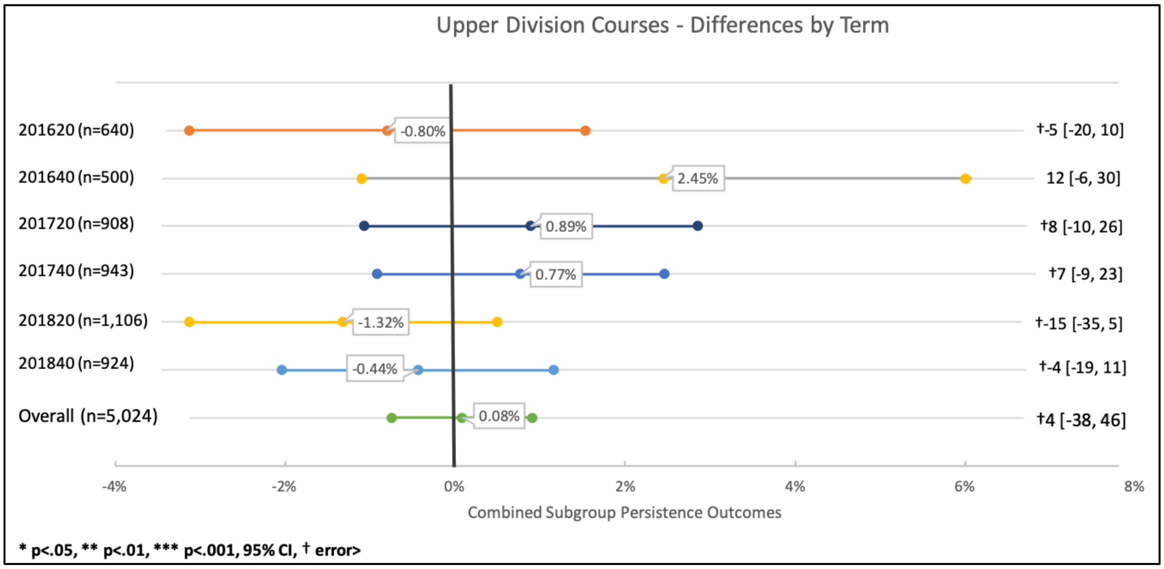

Figure 27. Upper division courses: Differences by term.

Hypothesis III (H_3) Difference in Difference Effects of Participation in SL Activities for Subgroup Populations of Students

The third hypothesis addressed the research question: Do the difference in student persistence mean scores vary based on subgroup populations of students who participate in the curricular HIP of SL?

Seminal research on success in higher education by Bean and Vesper (1992); Cabrera, Stampen, and Hansen (1990); Pascarella and Tenzini (2005); Tinto (1975, 1993); and more recently Seidman (2012, 2018) and Nash (1990) have provided empirical evidence on the influence of student input characteristics on student outcomes. This research question was designed to build on their prior research by investigating the local impacts of persistence on 25 categorically different student subgroup populations (e.g., gender, terms completed, part-time, first-time in college, etc.). The complete list of subgroups is found in Appendix A.

The null hypothesis of (H_3) states: There were no differential effects of categorical subgroup populations on persistence to the next term for students participating in SL activities at USU. This study independently analyzed 25 individual subgroup populations by categorizing them in the following course divisions: (1) combined lower- and upper-division courses, (2) lower-division courses, (3) upper-division courses. Additionally, each of the three categories and subgroups were analyzed by the following: (1) All six terms combined, (2) Spring 2016, (3) Fall 2016, (4) Spring 2017, (5) Fall 2017, (6) Spring 2018, and (7) Fall 2018. The PPSM methods used for this study concluded significant results of difference in persistence outcomes for subgroup populations in each of the three categories analyzed with significant ($p < 0.05$) and successful predictive model tests with errors $< \pm 0.03$. This study concluded overall differences in persistence outcomes for participating groups of students and their respective subgroup populations when compared to their counterparts, thus rejecting the stated null hypothesis of H_3.

Combined lower- and upper-division course subgroup population results. Table 9 provides an overview of the combined lower- and upper-division subgroup results.

Student input characteristics. The student input characteristics were held constant, and in accordance with the model, assumed participation in service learning courses influenced student outputs.

Female. Female gender was found to be significant ($p < 0.05$), and positively impacted when all terms were combined for analysis (see Tables F1.1, F1.2, and F1.5 for details). The overall effect for participating female students was a 1.84% increase in persistence on 5,030 analyzed students. The resulting unstandardized effect size and respective confidence intervals shows an average of 93 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 39 to 46 students.

When the Female subgroup population was independently analyzed by term, significant findings were realized in two terms: Spring 2016 (201620) and Fall 2017 (201740). A 3.5% increase on persistence for 617 student participants during 201620 resulted in an unstandardized effect size of 22 students retained after that term. Accounting for a 3.07% confidence interval

Table 9

Significant Subgroups of Combined Lower- and Upper-division Courses

Subgroup	All terms			Sp. 16			Fa. 16			Fa. 17			Sp. 18			Fa. 18		
	%	[CI]	*n*	%	[CI]	*n*	%	[CI]	*n*	%	[CI]	*n*	%	[CI]	*n*	%	[CI]	*n*
Academic level: undergraduate	1.35	[0.79]^3	8,926		NA			NA		2.92	[1.7]^3	1,562	1.89	[1.8]^1	2,023		NA	
Completed terms: 1-3 terms	1.76	[1.5]^1	3,022		NA			NA		5.32	[3.52]^2	397	3.72	[3.23]^1	825		NA	
Completed terms: 4+ terms	.98	[0.91]^1	4,795		NA			NA			NA			NA			NA	
Course modality: all on-ground		NA			NA			NA		2.77	[2.24]^1	896		NA			NA	
Course modality: all online		NA			NA			NA		12.26	[8.24]^2	117		NA			NA	
Course modality: mixed or blended	2.02	[1.24]^2	3,090		NA			NA			NA		3.24	[2.51]^1	791	2.79	[2.31]^1	550
Ethnicity: not Hispanic or Latino	1.34	[0.81]^2	8,666		NA			NA		2.93	[1.73]^3	1,527	1.91	[1.82]^1	1,982		NA	
Full-time vs. Part-time: full-time	1.25	[0.79]^2	7,949		NA			NA		2.4	[1.67]^2	1,383	1.9	[1.8]^1	1,782		NA	
Full-time vs. Part-time: part-time		NA			NA		-16.2	[12.25]^2	87	7.52	[6.77]^1	176		NA			NA	
Gender: female	1.84	[1.06]^3	5,030	3.5	[3.07]^1	617		NA		3.18	[2.2]^2	851		NA			NA	
Gender: male		NA			NA		-5.57	[4.2]^2	414	2.82	[2.65]^1	709		NA			NA	
Race: American Indian/Alaskan Native		NA			NA			NA		23.16	[21.32]^1	4		NA			NA	
Race: White or Caucasian	1.33	[0.83]^2	8,149		NA			NA		2.59	[1.76]^2	1,412	2.25	[1.87]^1	1,841		NA	
STEM Major: Not STEM	1.71	[0.96]^3	6,666		NA			NA		3.9	[2.05]^3	1,136		NA			NA	
STEM Major: STEM		NA			NA		-7.32	[5.64]^1	220		NA			NA			NA	
Undergraduate type: first time in college		NA			NA			NA			NA		3.04	[2.49]^1	1,102		NA	
Undergraduate type: transfer	2.69	[1.64]^2	2,153		NA			NA		5.34	[3.28]^2	416		NA			NA	

^{1} $p < .05$, ^{2} $p < .01$, ^{3} $p < .001$, 95% CI reveals a broad range of retained students from 3 to 41. A conservative view of these results leads me to expect at least a 0.43% positive impact, which is 0.35% lower than all terms combined. For Fall 2017, there was a 3.18% increase on persistence for 851 student participants resulting in an unstandardized effect size of 27 students retained after that term. Accounting for a 2.2% confidence interval reveals a broad range of retained students from 8 to 46. A conservative view of these results leads me to expect at least a 0.98% positive impact, which is 0.20% higher than all terms combined.

With exception to Fall 2018 (201840), which failed when the predictive model was tested, error > $\pm$ 0.03 (see Table F1.7), all other terms did not produce significant results $p <$ 0.05. Each analyzed term had sufficient participant students and eligible comparisons for adequate statistical power.

Male. When the Male gender subcategory was analyzed, there were only two terms with significant results, Fall 2016 (201640) and Fall 2017 (201740) (see Tables F1.1, F1.3, and F1.5 for details). Interestingly, data from 201640 produced a negative -5.57% decrease on persistence for 414 student participants resulting in an unstandardized effect size of -23 students lost after that term. Accounting for a 4.2% confidence interval reveals a broad range of lost students from -40 to -6. A conservative view of these results leads me to expect at least a -1.37% negative impact.

Whereas 201740 there was a positive 2.82% increase on persistence for 709 student participants resulting in an unstandardized effect size of 20 students retained that term. Accounting for a 2.65% confidence interval reveals a broad range of retained students from 1 to 39. A conservative view of these results leads me to expect at least a 0.17% positive impact, which is 1.20% higher than the only other significant term analyzed over the three years.

White or Caucasian. The White or Caucasian ethnic group was found to be significant and positively impacted when all terms were combined for analysis (see Tables F1.1, F1.5, and

F1.6 for details). The overall effect for students who participated from this ethnic subgroup was a 1.33% increase in persistence on 8,149 analyzed students. The resulting unstandardized effect size and respective confidence intervals, found in Table F1.1, shows an average of 108 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 41 to 176 students. When terms were independently analyzed, significant findings were realized after two terms, Fall 2017 (201740) and Spring 2018 (201820).

A 2.59% increase on persistence for 1,412 student participants during 201740 resulted in an unstandardized effect size of 37 students retained after that term. Accounting for a 1.76% confidence interval reveals a broad range of retained students from 12 to 61. A conservative view of these results leads me to expect at least a 0.83% positive impact, which is 0.33% higher than all terms combined.

For 201820 there was a 2.25% increase on persistence for 1,841 student participants resulting in an unstandardized effect size of 41 students retained after that term. Accounting for a 1.87% confidence interval reveals a broad range of retained students from seven to 76. A conservative view of these results leads me to expect at least a 0.38% positive impact, which is 0.12% lower than all terms combined.

Not Hispanic or Latino. The Not Hispanic or Latino ethnic group was found to be significant and positively impacted when all terms were combined for analysis (see Tables F1.1, F1.5, and F1.6 for details). The overall effect for students who participated from this ethnic subgroup was a 1.34% increase in persistence on 8,666 analyzed students. The resulting unstandardized effect size and respective confidence intervals, found in Table F1.1, shows an average of 116 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 46 to 186 students. When terms were independently analyzed significant findings were realized after two terms, Fall 2017 (201740) and Spring 2018 (201820).

A 2.93% increase on persistence for 1,527 student participants during 201740 resulted in an unstandardized effect size of 45 students retained after that term. Accounting for a 1.73% confidence interval reveals a broad range of retained students from 18 to 71. A conservative view of these results leads me to expect at least a 1.2% positive impact, which is 0.67% higher than all terms combined.

For 201820 there was a 1.91% increase on persistence for 1,982 student participants resulting in an unstandardized effect size of 38 students retained after that term. Accounting for a 1.82% confidence interval reveals a broad range of retained students from two to 74. A conservative view of these results leads me to expect at least a 0.09% positive impact, which is 0.44% lower than all terms combined.

American Indian/Alaskan Native. The American Indian/Alaskan Native ethnic group for Fall 2017 (201740) was found to be significant with a $p = 0.035$; however, the analysis failed the predictive model test with an error of 8.52% (see Table F1.1 for details). With exception to Fall 2018 (201840), all terms failed the predictive model test returning errors greater than $\pm$ 3%. Nevertheless, 201840 results were not significant. Consequently, there was insufficient evidence to interpret the results for the American Indian/Alaskan Native ethnic group.

First time in college. The First Time in College students were found to be significant and positively impacted for the Spring 2018 (201820) term (see Table F1.6 for details). The overall effect for the participating students was a 3.04% increase in persistence on 1,102 analyzed students. The resulting unstandardized effect size and respective confidence intervals was an average of 34 participating students were retained over the analyzed three years/six terms with confidence interval boundaries ranging from six to 61 students. When combined and individual terms were independently analyzed there were no significant findings realized. However, for each term analyzed there were adequate participant students for statistical power, and testing the predictive model returned no errors.

Transfer. The Transfer students were found to be significant and positively impacted when all terms were combined for analysis (see Tables F1.1 and F1.5 for details). The overall effect for the participating students was a 2.69% increase in persistence on 2,153 analyzed students. The resulting unstandardized effect size and respective confidence intervals, found in Table F1.1, shows an average of 58 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 23 to 93 students. When terms were independently analyzed significant findings were only found for Fall 2017 (201740).

A 5.34% increase on persistence for 416 student participants during 201740 resulted in an unstandardized effect size of 22 students retained after that term. Accounting for a 3.28% confidence interval reveals a range of retained students from nine to 36. A conservative view of these results leads me to expect at least a 2.06% positive impact, which is 1.01% higher than all terms combined.

With exception to Fall 2018 (201840), where details are found in Table F1.7, that failed the predictive model test with a 3.3% error and did not return significant results, all other terms successfully passed model testing and also did not produce significant results. Spring 2017, Fall 2017, Spring 2018, and Fall 2018 terms had sufficient participant students and eligible comparisons for adequate statistical power; however, Spring 2016 and Fall 2016 had less than 250 participating students and considered too small for valid analysis.

Institutional context characteristics. Combined groups of students enrolled in lower- and upper-division courses were also aggregated by subgroups using an institutional context such as terms, course modalities, part-time, etc. Each subgroup was held constant and independently analyzed.

Completed 1-3 terms. The students who Completed 1-3 Terms were found to be significant and positively impacted when all terms were combined for analysis (see Tables F1.1, F1.5, and F1.6 for details). The overall effect for the participating students was a 1.76% increase in persistence on 3,022 analyzed students. The resulting unstandardized effect size and respective confidence intervals, found in Table F1.1, shows an average of 53 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from six to 100 students. When terms were independently analyzed significant findings were realized after the following two terms, Fall 2017 (201740) and Spring 2018 (201820).

A 5.32% increase on persistence for 397 student participants during 201740 resulted in an unstandardized effect size of 21 students retained after that term. Accounting for a 3.52% confidence interval reveals a range of retained students from seven to 35. A conservative view of these results leads me to expect at least a 1.80% positive impact, which is 1.59% higher than all terms combined.

For 201820 there was a 3.72% increase on persistence for 825 student participants resulting in an unstandardized effect size of 31 students retained after that term. Accounting for a 3.23% confidence interval reveals a broad range of retained students from four to 57. A conservative view of these results leads me to expect at least a 0.49% positive impact, which is 0.28% higher than all terms combined.

All other individual terms were independently analyzed and there were no significant findings realized. Additionally, each term that was analyzed provided an adequate number of participant students for statistical power and predictive model testing returned no errors.

Completed 4+ terms. The students who Completed 4+ Terms were found to be significant and positively impacted when all terms were combined for analysis (see Table F1.1 for details). The overall effect for the participating students was a 0.98% increase in persistence on the 4,795 analyzed students. The resulting unstandardized effect size and respective confidence intervals shows an average of 47 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from three to 91 students. When terms were independently analyzed there were no significant findings realized.

Additionally, each term that was analyzed provided an adequate number of participant students for statistical power. Predictive model testing returned a 3.6% error for both Fall 2017 and Fall 2018 precluding their non-significant results from interpretation.

Course modality: All on-ground (see Appendix A for definition). The students who took only On-Ground courses were found to be significant and positively impacted for the Fall 2017 (201740) term (see Table F1.5 for details). The overall effect for the participating students was a 2.77% increase in persistence on 896 analyzed students. The resulting unstandardized effect size and respective confidence intervals shows an average of 25 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from five to 14 students. When combined and all other terms were independently analyzed there were no significant findings realized. Additionally, each term that was analyzed provided an adequate number of participant students for statistical power and predictive model testing returned no errors.

Course modality: All online. The students who took Online courses were found to be significant and positively impacted for the Fall 2017 (201740) term (see Table F1.5 for details). The overall effect for the participating students was a 12.26% increase in persistence on 117 analyzed students. The resulting unstandardized effect size and respective confidence intervals should be interpreted with caution due to the low number of analyzed participants. Results show an average of 14 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from five to 24 students. When combined and all other terms were independently analyzed they all failed the predictive model test with errors greater than $\pm$ 3.0% precluding their nonsignificant results from interpretation.

Course modality: Mixed or blended. The students who took Mixed or Blended courses (courses with both face-to-face and online or broadcast elements) were found to be significant and positively impacted when all terms were combined for analysis (see Tables F1.1, F1.6, and

F1.7 for details). The overall effect for the participating students was a 2.02% increase in persistence on 3,090 analyzed students. The resulting unstandardized effect size and respective confidence intervals shows an average of 62 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 24 to 101 students.

When terms were independently analyzed significant findings were realized after the following two terms, Spring 2018 (201820) and Fall 2018 (201840). A 3.24% increase on persistence for 791 student participants during 201820 resulted in an unstandardized effect size of 26 students retained after that term. Accounting for a 2.51% confidence interval reveals a broad range of retained students from six to 45. A conservative view of these results leads me to expect at least a 0.73% positive impact, which is 0.05% lower than all terms combined.

For Fall 2018 there were significant results, (p = 0.017); however, an error of 4.0% was determined when testing the predictive model. The error greater than $\pm$ 3.0% precludes this term's results from interpretation.

All other individual terms were independently analyzed, and no significant findings realized. Additionally, each analyzed term provided an adequate number of participant students for statistical power and predictive model testing returned no errors.

Full-time. The Full-Time students were found to be significant and positively impacted when all terms were combined for analysis (see Tables F1.1, F1.5, and F1.6 for details). The overall effect for the participating students was a 1.25% increase in persistence on 7,949 analyzed students. The resulting unstandardized effect size and respective confidence intervals shows an average of 99 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 37 to 162 students.

When terms were independently analyzed significant findings were realized after the following two terms, Fall 2017 (201740) and Spring 2018 (201820). A 2.4% increase on persistence for 1,383 student participants during 201740 resulted in an unstandardized effect size of 33 students retained after that term. Accounting for a 1.67% confidence interval reveals a broad range of retained students from 10 to 56. A conservative view of these results leads me to expect at least a 0.73% positive impact, which is 0.27% higher than all terms combined.

For 201820, there was a 1.9% increase on persistence for 1,782 student participants resulting in an unstandardized effect size of 34 students retained after that term. Accounting for a 1.8% confidence interval reveals a broad range of retained students from two to 66. A conservative view of these results leads me to expect at least a 0.10% positive impact, which is 0.36% lower than all terms combined.

All other individual terms were independently analyzed, and no significant findings realized. Additionally, each analyzed term provided an adequate number of participant students for statistical power and predictive model testing returned no errors.

Part-time. Two terms analyzed for the Part-Time students were found to have significant positive and negative impacts (see Tables F1.3 and F1.5 for details). A negative 16.2% decrease on persistence for 87 student participants during 201640 resulted in an unstandardized effect size of a negative 14 students lost after that term. The resulting unstandardized effect size and respective confidence intervals should be interpreted with caution due to the low number of analyzed participants. Accounting for a 12.25% confidence interval reveals a broad range of retained students from -25 to -3. A conservative view of these results leads me to expect at least a 3.95% negative impact on participating students.

For 201740 there was a 7.52% increase on persistence for 176 student participants resulting in an unstandardized effect size of 13 students retained after that term. The resulting unstandardized effect size and respective confidence intervals should be interpreted with caution due to the low number of analyzed participants. Accounting for a 6.77% confidence interval reveals a broad range of retained students from one to 25. A conservative view of these results leads me to expect at least a 0.75% positive impact.

Only the category using a combination of all terms had an adequate number of participant students for statistical power. Nevertheless, the analysis of the combined terms results was insignificant ($p = 0.243$). All individual terms were independently analyzed and there were no significant findings realized, nor were there adequate numbers of participant students for statistical power. Tests on predictive modeling for all combined and individual terms returned no errors.

Not STEM. The students who were enrolled into Not STEM majors were found to be significant and positively impacted when all terms were combined for analysis (see Tables F1.1 and F1.5 for details). The overall effect for the participating students was a 1.71% increase in persistence on 6,666 analyzed students. The resulting unstandardized effect size and respective confidence intervals shows an average of 114 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 50 to 178 students.

When terms were independently analyzed, significant findings were realized only for Fall 2017 (201740). For this term, a 3.9% increase on persistence for 1,136 student participants resulted in an unstandardized effect size of 44 students retained after that term. Accounting for a 2.05% confidence interval reveals a broad range of retained students from 21 to 68. A conservative view of these results leads me to expect at least a 1.85% positive impact, which is 1.10 % higher than all terms combined.

When the prediction modeling was tested on Fall of 2018 (201840) data, it produced an error of 3.14% and precluded its results from interpretation, while all other independently analyzed terms and combined terms returned no errors or significant results.

STEM. Students who were enrolled into STEM majors were found to be significant and negatively impacted for the Fall 2016 (201640) term (see Table F1.3). The overall effect for the participating students was a -7.32% decrease in persistence on 220 analyzed students. The resulting unstandardized effect size and respective confidence intervals should be interpreted with caution due to the low number of analyzed participants. The resulting unstandardized effect size and respective confidence intervals shows an average of -16 participating students were lost over the analyzed 3 years/6 terms with confidence interval boundaries ranging from -29 to negative four students. When combined and all other terms were independently analyzed there were no significant findings realized. Except for the Fall 2016 (201640) term, all terms provided an adequate number of participant students for statistical power. When prediction modeling was tested, Spring 2016 (201620) and Fall 2017 (201740) terms failed with an error greater than $\pm$3.0%, precluding their insignificant results from interpretation, while all other analyzed terms and combined terms returned no errors or significant results.

Lower course division descriptive statistics. Table 10 provides an overview of terms for the lower-division subgroup results.

Student input characteristics. The student input characteristics were held constant and independently analyzed. There were sufficient participants and comparison students enrolled in lower-division courses to interpret the following results.

Female. Female gender was found to be significant and positively impacted when all terms were combined for analysis (see Tables F2.1 and F2.6 for details). The overall effect for participating Female students was a 2.85% increase in persistence on 1,798 analyzed students. The resulting unstandardized effect size and respective confidence intervals shows an average of 51 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 11 to 91 students.

When terms were independently analyzed, significant findings were realized in only Spring 2018 (201820). Results for this term were found to be significant (p = 0.0478); however, the analysis failed the predictive model test with an error of -4.22% (see Table F2.1 for details). Additionally, Spring 2016 (201620) and Spring 2017 (201720) also failed the predictive model test, returning errors greater than $\pm$ 3%. All other analyzed terms passed the predictive model

Table 10

Significant Subgroups of Lower-Division Courses

	All Terms			Sp. 16			Fa. 16			Sp. 17			Fa. 17			Sp. 18			Fa. 18		
Subgroup	%	[CI]	*n*	%	[CI]	*n*	%	[CI]	*n*	%	[CI]	*n*	%	[CI]	*n*	%	[CI]	*n*	%	[CI]	*n*
Academic level: Undergraduate	2.61	[1.64]^{2}	3,290		NA			NA			NA			NA		4.76	[4.05]^{1}	643		NA	
Completed terms: 1-3 terms	2.82	[2.46]^{1}	1,608		NA			NA			NA			NA			NA			NA	
Completed terms: 4+ terms	4.39	[3.43]^{1}	713	10.98	[7.79]^{2}	143		NA			NA			NA			NA			NA	
Course modality: All on-ground	1.93	[1.89]^{1}	2,480		NA			NA			NA			NA			NA			NA	
Course modality: All online		NA			NA			NA			NA			NA			NA			NA	
Course modality: Mixed or blended	4.73	[3.35]^{2}	789		NA			NA			NA			NA		9.21	[7.03]^{1}	189	8.52	[7.73]^{1}	103
Ethnicity: not Hispanic or Latino	2.66	[1.66]^{2}	3,214		NA			NA			NA			NA		4.66	[4.07]^{1}	634		NA	
Full-time vs. part-time: Full-time	3.1	[1.66]^{3}	2,908		NA			NA			NA			NA		6.33	[4.2]^{2}	563		NA	
Full-time vs. Part-time: Part-time		NA			NA		-18.13	[17.7]^{1}	49		NA			NA			NA			NA	
Gender: Female	2.85	[2.23]^{1}	1,798		NA			NA			NA			NA		5.91	[5.85]^{1}	322		NA	
Gender: Male		NA			NA			NA			NA			NA			NA			NA	
Race: American Indian/ Alaskan Native		NA			NA			NA			NA			NA			NA			NA	
Race: White or Caucasian	2.74	[1.73]^{2}	2,949		NA			NA			NA			NA		5.4	[4.32]^{1}	576		NA	
STEM Major: Not STEM	2.74	[1.92]^{3}	2,726		NA			NA			NA			NA		5.32	[4.79]^{1}	529		NA	
STEM Major: STEM		NA			NA			NA		8.49	[8.46]^{1}	110		NA			NA		6.16	[5.14]^{1}	100
Undergraduate Type: First Time in College	2.73	[1.84]^{2}	2,520		NA			NA			NA			NA		6.57	[4.61]^{2}	495		NA	
Undergraduate Type: Transfer		NA			NA			NA			NA			NA			NA			NA	

^{1} $p < .05$, ^{2} $p < .01$, ^{3} $p < .001$, 95% CI.

test; however, they did not produce significant results less than $p = 0.05$. When independently analyzing Female subgroups of students, only Spring 2016 (201620) had insufficient participants with $n = 221$ which, for this study, is not considered adequate for statistical power.

White. The White ethnic group was found to be significant and positively impacted when all terms were combined for analysis (see Tables F2.1and F1.6 for details). The overall effect for the participating ethnic students was a 2.74% increase in persistence on 2,949 analyzed students. The resulting unstandardized effect size and respective confidence intervals, found in Table F2.1, shows an average of 81 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 30 to 132 students.

When terms were independently analyzed, significant findings were realized after Spring 2018 (201820). For this term, there was a 5.4% increase on persistence for 576 student participants resulting in an unstandardized effect size of 31 students retained after that term. Accounting for a 4.32% confidence interval reveals a broad range of retained students from six to 56. A conservative view of these results leads me to expect at least a 1.08% positive impact, which is only 0.07% higher than all terms combined.

All other individual terms were independently analyzed, and there were no significant findings realized. Except for Spring 2017 (201720), which resulted in a -3.30% error, each analyzed term provided an adequate number of participant students for statistical power and predictive model testing that returned no errors.

Not Hispanic or Latino. The Not Hispanic or Latino ethnic group was found to be significant and positively impacted when all terms were combined for analysis (see Tables F2.1and F1.6 for details). The overall effect for the participating ethnic group of students was a 2.66% increase in persistence on 3,214 analyzed students. The resulting unstandardized effect size and respective confidence intervals, found in Table F2.1, shows an average of 85 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 32 to 139 students.

When terms were independently analyzed significant findings were realized after Spring 2018 (201820). For this term, there was a 4.66% increase on persistence for 634 student participants resulting in an unstandardized effect size of 30 students retained after that term. Accounting for a 4.07% confidence interval reveals a broad range of retained students from four to 55. A conservative view of these results leads me to expect at least a 0.59% positive impact, which is 0.41% lower than all terms combined.

All other individual terms were independently analyzed, and no significant findings were realized. With exception to Spring 2017 (201720), which resulted in a -3.47% error, each analyzed term provided an adequate number of participant students for statistical power and predictive model testing that returned no errors.

First time in college. The First Time in College students were found to be significant and positively impacted when all terms were combined for analysis (see Tables F2.1and F1.6 for details). The overall effect for the participating students was a 2.73% increase in persistence on 2,520 analyzed students. The resulting unstandardized effect size and respective confidence intervals, found in Table F2.1, shows an average of 69 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 22 to 115 students.

When terms were independently analyzed, significant findings were realized after Spring 2018 (201820). For this term, there was a 6.57% increase on persistence for 495 student participants resulting in an unstandardized effect size of 33 students retained after that term. Accounting for a 4.61% confidence interval reveals a broad range of retained students from 10 to 55. A conservative view of these results leads me to expect at least a 1.96% positive impact, which is 1.07% higher than all terms combined.

All other individual terms were independently analyzed, and no significant findings were realized. With exception to Spring 2017 (201720), which resulted in a -3.93% error, each analyzed term provided an adequate number of participant students for statistical power and predictive model testing that returned no errors.

Institutional context characteristics. Student subgroups were aggregated using an institutional context such as; terms, course modalities, part-time, etc. Each subgroup was held constant and independently analyzed.

Completed 1-3 Terms. The students who completed 1-3 terms were found to be significant and positively impacted when all terms were combined for analysis (see Table F2.1 for details). The overall effect for the participating students was a 2.82% increase in persistence on 1,608 analyzed students and significant (p = 0.0249) results. However, the analyzed term failed the predictive model test resulting in a -3.06% error. The error is slightly above the recommended 3.0% threshold and should be considered with caution. The resulting unstandardized effect size and respective confidence interval of 2.46% shows an average of 45 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 6 to 85 students.

Testing the predictive model for Spring 2016 (201620), Spring 2017 (??), and Spring 2018 (201820) failed by returning errors greater than $\pm$ 3%. All other analyzed terms passed the predictive model test; however, they did not produce significant results less than p = 0.05. The Fall 2016 (201640) and Fall 2017 (201740) terms passed the predictive model test; however, they did not have sufficient number of participant students for statistical power, nor did they return significant results.

Completed 4+ terms. The students who Completed 4+ Terms were found to be significant and positively impacted when all terms were combined for analysis (see Table F2.1 and F2.2 for details). The overall effect for the participating students was a 4.93% increase in persistence on 713 analyzed students. The resulting unstandardized effect size and respective confidence intervals shows an average of 31 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from seven to 56 students.

When terms were independently analyzed, significant findings were realized after Spring 2016 (201620). For this term, there was a 10.98% increase on persistence for 143 student participants resulting in an unstandardized effect size of 16 students retained after that term. Accounting for a 7.79% confidence interval reveals a range of retained students from 5 to 27. A conservative view of these results leads me to expect at least a 3.19% positive impact, which is 2.23% higher than all terms combined. However, this term failed the predictive model test resulting in a 3.01% error. The error is slightly above the recommended $\pm$ 3.0% threshold and should be considered with caution. Additionally, there were only n = 143 analyzed participant students, meaning results may also be suspect due to low statistical power. Nevertheless, the results were considered significant (p = 0.006).

All other independently analyzed terms of subgroups of students who completed 4+ terms did not have n > 250 for adequate statistical power nor did they return significant results. Additionally, when the predictive model was tested, Fall 2016 (201640) failed with a -4.09% error and was not considered for interpretation.

Course modality: All on-ground. The students who took only On-Ground courses were found to be significant and positively impacted when all terms were combined for analysis (see Table F2.1 for details). The overall effect for the participating students was a 1.93% increase in persistence on 2,480 analyzed students. The resulting unstandardized effect size and respective confidence intervals shows an average of 48 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from one to 95 students. When combined and all other terms were independently analyzed, there were no significant findings realized. Additionally, each analyzed term provided an adequate number of participant students for statistical power. Predictive model testing returned errors greater than $\pm$ 3.0% for

Spring 2016 (201620) and Spring 2017 (201720); whereas all other terms passed with no errors.

Course modality: Mixed or blended. The students who took Mixed or Blended courses were found to be significant and positively impacted when all terms were combined for analysis (see Tables F2.1, F2.6, and F2.7 for details). The overall effect for the participating students was a 4.73% increase in persistence on 789 analyzed students. The resulting unstandardized effect size and respective confidence intervals shows an average of 37 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 11 to 64 students.

When terms were independently analyzed, significant findings were realized after the following two terms, Spring 2018 (201820) and Fall 2018 (201840). However, the Spring 2018 and Fall 2018 terms failed the predictive model tests resulting in errors greater than $\pm$ 3.0%. Additionally, there were low numbers of analyzed participant students, meaning results may also be suspect due to low statistical power.

All other independently analyzed terms of student subgroups who took mixed or blended courses did not have $n > 250$ for adequate statistical power nor did they return significant results.

Full-time. The Full-Time students were found to be significant and positively impacted when all terms were combined for analysis (see Tables F2.1 and F2.6 for details). The overall effect for the participating students was a 3.1% increase in persistence on 2,908 analyzed students. The resulting unstandardized effect size and respective confidence intervals shows an average of 90 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 42 to 138 students.

When terms were independently analyzed, significant findings were realized for Spring 2018 (201820). A 6.33% increase on persistence for 563 student participants during 201820 resulted in an unstandardized effect size of 36 students retained after that term. Accounting for a 4.2% confidence interval reveals a broad range of retained students from 12 to 59. A conservative view of these results leads me to expect at least a 2.13% positive impact, which is 0.69% higher than all terms combined.

All other individual terms were independently analyzed, and no significant findings were realized. Additionally, each term analyzed provided an adequate number of participant students for statistical power. Except Spring 2017 (201720) that returned an error of -3.61%, predictive model testing returned no errors for the other nonsignificant terms.

Part-time. The Part-Time students who participated in SL courses during Fall 2016 (201640) were found to be significant and negatively impacted (see Table F2.3 for details). The overall effect for the participating students was a -18.13% decrease in persistence on 49 analyzed students. When the predictive model was tested for the term, it failed with a -4.8% error along with very low statistical power. Spring 2016 (201620) also failed the predictive model test and all other terms had too few participants for sufficient statistical power.

For the analyzed subgroup of Part-Time students only the combined terms with a $n = 374$ had sufficient statistical power and passed the predictive model test with insignificant ($p = 0.7395$) results deeming there was no difference.

Not STEM. The students who were enrolled into Not STEM majors were found to be significant and positively impacted when all terms were combined for analysis (see Tables F2.1 and F1.6 for details). The overall effect for the participating students was a 2.74% increase in persistence on 2,726 analyzed students. The resulting unstandardized effect size and respective confidence intervals shows an average of 75 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 22 to 127 students. When terms were independently analyzed significant findings were realized for Spring 2017 (201720) and Spring 2018 (201820).

Spring 2017 (201720) there was an 8.49% increase on persistence for 110 student participants resulting in an unstandardized effect size of 9 students retained after that term. The low number of analyzed participants (*n* = 110) did not provide sufficient statistical power and should be interpreted with caution.

Spring 2018 (201820) there was a 5.32% increase on persistence for 529 student participants resulting in an unstandardized effect size of 28 students retained after that term. Accounting for a 4.79% confidence interval reveals a broad range of retained students from three to 53. A conservative view of these results leads me to expect at least a 0.53% positive impact, which is 0.29% lower than all terms combined.

STEM. The students who were enrolled into STEM majors were found to be significant and positively impacted for the Spring 2017 (201720) and Fall 2018 (201840) terms (see Tables F2.4 and F2.7 for details). Results for 201720 were not considered for interpretation due to a -3.72% error when conducting a test on the predictive model. However, significant results for 201820 shows the effect on participating students was a 6.16% increase in persistence on 100 analyzed students. However, these results should be interpreted with caution due to the low number of analyzed participants and limited statistical power. Only the combined terms had adequate participants for statistical power and resulted in insignificant results.

Upper course division descriptive statistics. The analyzed data for subgroups in upper-division courses is summarized in Table 11, where only three subgroups of student data produced significant results during the Fall 2016 and Spring 2017 terms.

Student input characteristics. The student input characteristics were held constant and independently analyzed. There were sufficient participants and comparison students enrolled in upper-division courses to interpret the following results.

Female. Female gender was found to be significant and positively impacted during Fall 2016 (201640) (see Table F3.3 for details). The effect for participating Female students during 201640 was a 4.85% increase in persistence on 271 analyzed students. The resulting unstandardized effect size and respective confidence intervals shows an average of 13

Table 11

Significant Subgroups of Upper-Division Courses

	Fa. 16			Sp. 17		
Subgroup	%	[CI]	n	%	[CI]	n
Gender: Female	4.85	[4.44] [1]	271		NA	
STEM Major: Not STEM	5.66	[3.84] [2]	356		NA	
Undergraduate Type: Readmit		NA		3.57	[3.43] [1]	232

[1] $p < .05$, [2] $p < .01$, 95% CI.

participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from one to 25 students. When terms were independently analyzed, significant findings (p = 0.032) were realized in 201640.

With exception to Spring 2017 (201720) and Fall 2016 (201640), all other terms failed the predictive model test with an error greater than $\pm$ 3.0% (see Table F3.1 for details). Nevertheless, all terms analyzed had greater than 250 participant Female students, creating sufficient statistical power to conduct the analysis.

Not STEM. The students who were enrolled into Not STEM majors were found to be significant and positively impacted during Fall 2016 (201640) (see Table F3.3 for details). The effect for participating Not STEM students during 20140 was a 5.66% increase in persistence on 356 analyzed students. The resulting unstandardized effect size and respective confidence intervals shows an average of 20 participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from 6 to 34 students. When the terms were independently analyzed significant findings (p = 0.004) were realized in only 201640.

With exception to Spring 2017 (201720) and Fall 2016 (201640), all other terms failed the predictive model test with an error greater than $\pm$ 3.0% (see Table F3.1 for details). Nevertheless, all terms analyzed had greater than 250 Not STEM student participants, creating sufficient statistical power to conduct the analysis.

Readmitted. The Readmitted students (students who left USU for a time [without filing a Leave of Absence] and return after re-applying to USU) were found to be significant and positively impacted during Spring 2017 (201720) and Spring 2018 (201820) (see Tables F3.4 and F3.6 for details). When the predictive model was tested, 201820 failed with an error of 4.02%, while 201720 passed. The effect for participating Readmitted students during 201720 was a 3.57% increase in persistence on 232 analyzed students; however, caution should be used interpreting results with questionably low statistical power. The resulting unstandardized effect size and respective confidence intervals shows an average of eight participating students were retained over the analyzed 3 years/6 terms with confidence interval boundaries ranging from zero to 16 students. When terms were independently analyzed, significant findings ($p = 0.041$) were realized in 201720.

With exception to 201720 and Fall 2016 (201640), all other terms failed the predictive model test with an error greater than $\pm$ 3.0% (see Table F3.1 for details). Nevertheless, all other terms, except 201720, had greater than 250 participant students and sufficient statistical power to conduct the analysis.

Conclusion

After analysis of 3 years/6 terms of historical data, it was possible to answer the three research questions proposed for this study with significant results. When comparing groups of participating students with their statistically equivalent counterparts, significant results of this study found mostly positive impacts on persistence to the next term for participating students. Interestingly, when aggregating lower- and upper-division students, only one subgroup of Male students provided interpretable and negative results. These unique findings illustrated how Male student participants left USU as a result of taking a SL course; whereas, all other subgroups resulted in positive or inconclusive impacts on persistence.

The PPSM methods used for this study provided detailed insights of the planned comparison research questions designed to investigate *what* impacts were had on student participants in SL courses. The next chapter will interpret the results and further discuss implications and conjecture *why* the USU students experienced the found results.

CHAPTER V

DISCUSSION

Throughout history, government officials and academic leaders have been expected to cultivate a strong society and economy by educating and credentialing individuals (Topper & Howard, 2017). Educational attainment has illustrated positive effects on personal advancement and social mobility for individuals who have obtained a baccalaureate degree (Bourdieu, 1974; Freedman, 2017; Labaree, 1997). This study supports the accountability demands placed on academic leaders to develop curriculum and instruction to produce optimal student outcomes. This study employed a quasi-experimental research design investigating whether locally designed SL courses contributed to or inhibited student outcomes.

Results of this research study are intended to contribute to an existing body of student success research by investigating the impacts of SL activities on student groups at USU. Student participation in the HIP of SL activities is known to generally result in positive persistence outcomes of student in higher education (Howe & Fosnacht, 2017; Kinzie & Kuh, 2017). With a charge to improve institutional performance metrics, Utah's Commissioner of Higher Education and Board of Regents mandated all its institutions to provide HIP opportunities for their students with expectations to increase graduation rates and reduced time to completion (Buhler, 2017). Despite the investments of valuable resources necessary to design and implement the mandated HIP activities, relatively little is known regarding the local impacts of these activities within the Utah institutions.

Most student success research focuses on internal and external contributing factors on an individual's abilities to persist (Kuh, et al., 2006) and less on the specific elements of intentionally designed experiences, like a SL curriculum, that are expected to positively impact persistence. Even more so, there is little known about the local impacts of HIP-SL experiences on categorical group populations of participant students such as course modality, first time in college, STEM etc. (see Appendix A) beyond general demographics (J. Kinzie, personal communication, September 17, 2019).

Study Synopsis

Through this research study, effort was made to overcome limitations in the literature and investigate the impacts of a SL curriculum on students' persistence to the next term. Particularly, an investigation of planned comparisons of specific impacts on various categorical divisions of students and subgroup populations were conducted. The research questions were designed to be directional a priori, as grounded in cited theories on student success, and used to guide the planned comparisons and interpret the results. Additionally, the granular term-by-term based results, in aggregate, were used to investigate the research questions, but independently provided both planned and exploratory comparisons that may be used to promote further research in SL.

The overall results of this study on the impacts of the locally designed and implemented SL activities fill gaps in HIP research. These gaps can be attributed to the lack of availability of resources necessary to feasibly conduct this type of analysis. The PPSM methods required a machine learning infrastructure and access to unprecedented amounts of data to employ advanced statistical techniques used to discover student outcomes. The intent was to examine the impacts of persistence on categorical populations of students who participated in deliberately designed SL courses at USU. This study also intended to add discovered information to the existing body of research literature in the field of student success, and to demonstrate the efficiency of using advanced methods of learning analytics to operationalize ongoing research and analysis of extant HIP activities in higher education.

Astin and Antonio's (2012) inputs, environment, and outputs (IEO) conceptual model was used to structure research methodology and a groundwork of theories pertaining to student persistence and degree completion (Bourdieu, 1974; Kuh et al., 2006; Nora & Cabrera, 1996; Seidman, 2018; Tinto 1975, 1993). In support of a HIP perspective, which is intended to be interdisciplinary (Ehrenberg & Smith, 2016; Goldrick-Rab et al., 2009; Kuh, 2013; Tinto, 2012), multiple interdisciplinary theories were used to account for student and institutional level influences. To minimize self-selection bias in the estimation of SL participation effects, propensity and prediction score matching techniques were employed using the advanced PPSM methods (Kil, Chan, et al., 2017).

Historical and undergraduate student-level data used for this analysis was drawn from 3 years/6 terms of students enrolled at USU. Student participants were found in 254 USU courses that followed an approved SL curriculum. Control groups of students available for analysis were taken from students who opted not to take SL courses ($N = 108{,}338$). The final sample of analyzed student participants available for this study encompassed $N = 8{,}959$, and $n = 8{,}948$ of them were successfully matched with control students to determine comparison results.

Major Findings and Discussion of Analysis Results

In the following section, the three primary research questions will be used to present the major findings. First, the overall impacts of persistence on a combination of all student participants from lower- and upper-division courses will be discussed. Second, an interpret ion of results for lower- and upper-division courses were independently analyzed and compared for analysis. Third, a discussion of the significant impacts of persistence on independently analyzed categorical subgroups of students.

Overall Impacts of Combined Divisions of Students

The first research question leverages the greatest statistical power of the three research questions by comparing all eligible students from all SL courses across a 3-year timeframe. The research question was designed to investigate a priori directionally positive assumptions based on prior HIP research and student persistence (Kuh, 2013). The question reads: Does participation in the curricular HIP of SL have a significantly positive difference in the means on students' likelihood to persist to the next term? In this analysis, outcome measures of participating and control groups were compared by analyzing all combined terms, and then independently analyzing each of the available six terms.

One of the salient findings of this research question supports prior HIP research results that demonstrated positive impacts of persistence on students who participated in SL activities (Kuh, 2013; Howe & Fosnacht, 2017; Strategic Initiatives, 2018). The generalizable positive results were confirmed when analyzing the impacts on USU students who participated in the local implementations of SL courses. When participating students were compared to their statistically identical counterparts, results demonstrate a positive impact of a 1.34% difference in student persistence outcomes. Accounting for the significance of $p = 0.0009$, there is a high probability that participation in USU courses that apply an approved SL curriculum will promote persistence across the general population. While these results are significant, $p < 0.05$, statistical significance testing alone does not provide the necessary information for interpreting the magnitude of the impacts and its precision (Nakagawa & Cuthill, 2007). As such, the unstandardized effect size for this analysis demonstrates an average of 120 USU students over the 3 years were retained as a result of participating in a course that applied a SL curriculum. Accounting for a calculated 95% confidence interval illustrates a range of students between 48 on the low end and 191 on the top boundary.

The number of retained students can be translated to a practical and meaningful unstandardized effect size as retained tuition dollars. USU's business and finance department for the years of 2018/2019 provided an average retained annual tuition multiplier of $4,544 for undergraduate students. After applying this multiplier with a relatively conservative average number of 120 retained overall participating students across 3 years, a total of $545,280 ($181,760 per year) was retained by the institution as a result of SL.

The overall positive results validate prior longitudinal research and confirms that USU's implementation of HIP-SL courses during the last 3 years has retained tuition dollars. However, the aggregated 3-year results do not provide sufficient detail for meaningful improvement of SL curriculum. The National Center for Public Policy and Higher Education promotes continuous course redesign practices to reduce the cost of instruction and positively impact student retention (Twigg, 2005). In support of curricular improvement by reflecting on student outcomes, this research design provides details from independently analyzed term-based results to illuminate realized outcome differences with greater fidelity, which could result in more informed decisions.

Further term-based analysis was conducted to interpret combined division results (see Figure 15). In Figure 15, *overall* results are on the bottom line and includes all terms and it is intended to provide a relative baseline whereby all other terms can be compared for interpretation. Each term was independently analyzed to calculate respective significance and unstandardized effect size results. When combined divisions of students' data were independently analyzed for each of the six available terms, only Fall 2017 and Spring 2018 produced interpretable results. Additionally, each of the six terms had a sufficient number of participants for statistical power and no errors were found when the predictive model was tested, meaning there was sufficient variance between the analyzed groups of students; however, only two terms showed significant differences between the compared means.

Nothing in the data or student success theories explains the term-based differences; however, after investigating institutional metrics of retention during the academic year of 2018 (which includes Fall 2017 and Spring 2018), similar positive outcomes of retention were realized across the institution. University-wide retention statistics during that same academic year realized a dramatic 3.7 percentage point increase in retention for a cohort of undergraduate students in 2019. Notably, there were 3,594 undergraduate students who participated in SL courses during that year, and there were 3,487 undergraduate cohort students. Unfortunately, the participant data used for this analysis cannot be used to associate students who participated in SL courses with the cohort. Therefore, it was unable to be determined whether SL participation had any impact on the dramatic increase. Nevertheless, results from this analysis show an average of 2.99% of participant students persisted from Fall 2017 to Spring 2018 and 1.87% from Spring 2018 to Fall 2018. The average unstandardized effect size of retained tuition dollars from the impacts of SL courses that year was $386,240, more than twice the amount of the comparable 3-year baseline average of $183,275.

The results of combined divisions of students during the academic year of 2018 merits further research to investigate why the cohort experienced a large increase in retention after those terms. Another factor to consider, USU set out to obtain the Carnegie classification of Community Engaged Learning in 2018; this new initiative required organizational changes along with other administrative decisions to prepare for this endeavor. Using theories of leadership and organizational change (Bass, 2010; Bolman & Deal, 2015; Jago, 1982; Kotter, 1996) as a theoretical groundwork for research, can be used to investigate the organizational decisions to determine whether it influenced the positive changes in retention outcomes during those terms.

Comparison of Impacts Between Lower- and Upper-Divisions Courses

This study's second research question independently analyzed students enrolled in either upper- and lower-division courses. The design of this question was based on research methodology by Alexander Astin (1970) for which he used statistical techniques to investigate the impacts of college environments on students. When he provided a rationale for separating student divisions for analysis he stated, "The findings from these studies are very difficult to interpret, primarily because of problems in research design and methodology" (Astin, 1970, p. 223). Methodology for this research question was designed to add greater detail to investigate a priori comparison of differences between students in the lower- and upper-division courses. The question reads: Is there a significant difference in the student persistence mean values based on SL course levels (e.g., lower division or upper division)? Following the conceptual model, course participants were organized to be mutually exclusive by categorically dividing them into respective course divisions and made available for analysis. There were also two pools of control groups of students that were mutually exclusive by only being enrolled in upper or lower division courses, and they were eligible for analysis as long as they were enrolled during the same terms as the participant students. Outcome measures of this analysis compared an aggregate of participants from all overall combined terms and were then independently analyzed using each of the available six terms for both lower- and upper-division courses.

It was hypothesized there would be persistence outcome differences of participating lower- and upper-division courses of students (Astin, 1970, 1985). As illustrated in Figure 22, the lower-division group of students realized a 2.61% positive difference of persistence when compared to their control counterparts; however, there were insufficient results of statistical significance to interpret results of the upper-division group of students. Upon further investigation of the analysis for the overall combined terms of upper-division students, the predictive model test returned a 3.4% error and reinforced the non-significant outcome results as insufficient for interpretation. Consequently, Null H_2 was not fully accepted or rejected due to insufficient statistical results for upper-division students. The overall analysis of this question only partially validates prior research from:

- Astin (1970, 1985) whose analysis indicated that differences between the divisions of students should have been realized.
- Kuh et al. (2017) who posited an overall expected positive impact of persistence for all participating students.

Lower-division analysis. When the overall results from the first research question were used as a baseline for comparison to the lower division of students, there was a substantial positive impact on the lower division of students with a notable statistical significance, (p = 0.0019*).* Interpretation of unstandardized effect sizes illustrates a financial comparison of estimated retained tuition dollars; the lower-division students retained $390,784, and the combined division of students, which also included the lower-division students, retained $549,824 tuition dollars over the 3-year timeframe. The baseline of combined divisions is not mutually exclusive of the lower-division outcome results. Interestingly, when dividing the overall retained dollars by analyzed students the combined divisions showed $61 per student, whereas the lower-division student retained almost double that amount at $119 per student. Even though this study was unable to interpret the impacts of SL courses on upper- division course students, it does indicate the value of institutional investments into lower-division SL courses.

Upper-division analysis. After further analysis of the overall (combined terms) and the individual-term statistical results for the upper-division courses (see Figure 25), patterns emerged that signified problems preventing interpretation. The patterns were realized after following a pre-determined process of interpreting results. Before the results were interpreted, a process of elimination used three guiding questions that must be satisfied, otherwise the analyzed results were deemed suspect and insufficient for interpretation:

1. Was there a sufficient number of participant students (greater than 250) for adequate statistical power?
2. Are the results statistically significant with an alpha less than either 0.05, 0.01, or 0.001?
3. Was there an error with a distance greater than $\pm$ 0.03 from the predicted counterfactual and the actual outcome for the control group?

When the three questions were used to test the overall results, there was an adequate number of participants (n = 5,024) for statistical power, but the results were insignificant (p =

0.8575) and produced a failed predictive model returning a 3.4% error. After applying the same process to each individually analyzed term, insignificant results were identified along with errors in the predictive model for all terms, except Fall 2016. In comparison to independently analyzed terms from the lower-division, there was only one term (Spring 2017) that failed both significance and predictive model testing after analyzing eligible students from the lower-division courses.

The seemingly bipolar results promoted deeper investigation of the predictive model and its capacity to evaluate upper-division student groups. Performance of the predictive model is dependent on the variability of student characteristics (Kil, Chan, et al., 2017). However, upper classman (Juniors and Seniors) at USU have shown very little variability in their persistence outcomes than their lower classman (Freshman and Sophomores) counterparts. Furthermore, the model did not adequately predict outcomes of high-performing upper classman because they have even less variability in their outcomes, which does not illustrate model accuracy, only its dependence on variability (M. Colver, personal communication, September 12, 2019). Consequently, the analyzed results illustrated predictive model effectiveness for selected populations that have adequate variability.

This study benefitted from following Astin's (1975) methodological suggestions to separate class divisions for interpretation. While the PPSM methods were unable to provide interpretable results for the participants in upper-division courses, it did elicit meaningful insights of persistence outcomes realized by participating students in the lower-division courses. One of the greatest threats to statistical power in the methods used for this study was a fixed caliper width and bootstrapping without replacement that reduced variance and available students for analysis. However, this methodological strategy of categorically separating student data into divisions produced results illustrating a rationale for greater confidence in statistically significant results found in this study. Consequently, when exclusively separating groups of students' data, the model was able to identify variance in USU's student populations, thus adding to its value when investigating categorical subgroup characteristics.

Comparison of Impacts Between Student Subgroup Characteristics

Results from the first research question provided an aggregated overall positive impact of persistence for participating students across all years, terms, and subgroups. Then, when students were categorically separated using either lower- or upper-division course enrollments, the results illustrated significant impacts on the lower-division students; whereas, the PPSM model was unable to identify adequate variance and provide interpretable results from student enrollments in upper-division courses.

The third research question was designed to provide the greatest amount of detail to inform university administrators which student categorical subgroups realized the greatest impacts from participating in SL courses at USU. The research question reads: Do the difference in student persistence mean scores vary based on subgroup populations of students who participate in the curricular HIP of SL? Outcome measures for this analysis build on the prior two research questions by investigating subgroups of students. Methods of analysis guided by the first research question included an aggregate of combined divisions. The second research question categorically separated students enrolled in either lower- or upper-division courses.

Data analysis for the third research question used a different approach, when compared to most scholarly work on student persistence, where all student and institution-level influences were controlled and analyzed by each categorical subgroup of students collectively across three academic years and independently for each term. To assist with interpretation of significant results, the subgroups were organized by student-level inputs (e.g., gender, ethnicity, first-time in college, or transferring from another institution), or institution-level characteristics (e.g., course delivery type, terms completed, admitted to a STEM-related degree, or full and part-time).

Subgroups of combined lower- and upper-course divisions. To answer this question the student data was organized by combining groups of participating students enrolled in either a lower- or upper-division SL course and across all terms. By so doing, there was greater opportunity for statistical power (significant results) and to establish baseline values that were used to compare independently analyzed term-based results.

When enrolled participants from lower- and upper-division courses were combined and compared to an eligible pool of control students, nine of the 25 subgroups emerged with significant and interpretable results. As illustrated in Figure 28, seven subgroups (Transfer, Blended, Female, Not STEM, not Hispanic or Latino, White or Caucasian, and Full Time) resulted in significant results ($p \leq 0.01$). For this question, subgroups with $p \leq 0.05$ were interpreted with caution, and $p < 0.01$ with sufficient probability to represent respectively analyzed subgroups of students.

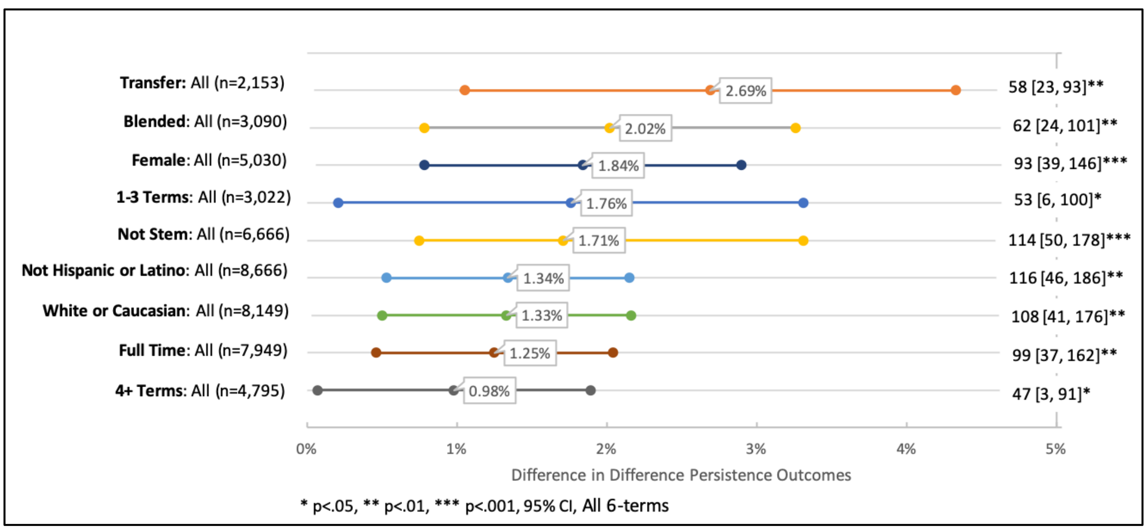

Figure 28. Subgroups of combined lower- and upper-division courses for all terms.

Ethnic subgroup. Ethnic subgroup results did not provide any sort of variety or differences due to a dominant population of White, and Not Hispanic or Latino student participants. For this study, 97% of the analyzed SL participants were not Hispanic or Latino, and

91% were White or Caucasian. As illustrated in Table 7, the only notable descriptive insight regarding ethnic subgroups was that SL course participants had nine percentage points more White students than the university average during the analyzed timeframe. There was ethnic representation from each subgroup and all but the White subgroup showed a smaller percentage of participants than the university average.

More than any other student-input characteristic, students who transferred to USU (Transfer) realized the greatest impact on persistence when compared to their counterparts. Over the 3-year timeframe, SL participation produced an average of 58 persisting students resulting in $263,552 retained dollars. The results are in line with other recent retention research on transfer students, showing positive impacts when they participated in HIPs (Thomas, Walsh, Torr, Alvarez, & Malagon, 2018). The positive outcomes on transfer students in USU SL courses merits further investigation to understand whether the persistence behaviors are correlated with a greater connection to the local community, peer students, and faculty.

Gender subgroup. The most notable student characteristic (see Figure 29) emerging from this study is the positive impacts on Female student participants. During the three-year analysis timeframe, the USU Female population was 47%. During the same timeframe, there was a higher proportion (56%) of Female participants in SL courses. Independent analysis of the combined terms and genders resulted in highly significant ($p = 0.0007$) and positive results from 93 persisting Female students over the 3 years. This equates to retaining $422,592 in tuition. When independently analyzing term-based results, Female student participants consistently experienced positive outcomes of persistence across the 3 years/6 terms.

In contrast, an overall analysis of their male counterparts ($n = 3{,}915$) did not return significant or interpretable results. However, when independently analyzing term-based results for the male students, Fall 2016 provided significant ($p = 0.0094$) and negative results showing a 5.57% of male SL participant students leaving USU after that term. From the whole of this study,

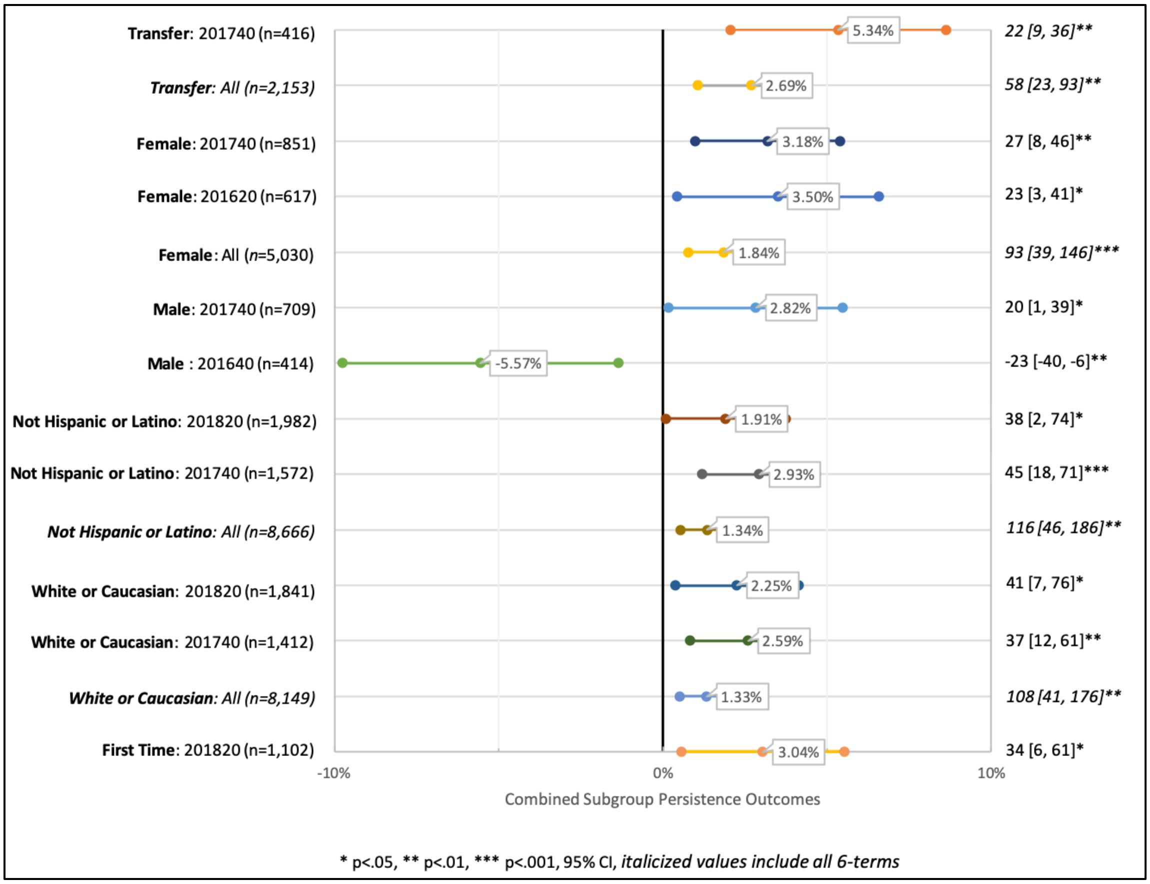

Figure 29. Subgroups of combined lower- and upper-division courses by terms and student inputs.

this is the largest and most significant negative outcome of any subgroup analyzed across the 3 years/6 terms. The average unstandardized effect size demonstrated that 23 Male students left USU after taking a SL course in Fall 2016 and have not yet returned. The resulting impacts on lost tuition, using a $2,272 term-based multiplier, was $-52,256. Putting this into context, the following Fall 2017 illustrated a correction, with significant results, and an increase in persistence by positively impacting 20 male students and retaining and estimated $45,440 of tuition.

Contrasting the differences in gender-based persistence results with the relatively flat and positive trending 7-year graduation rates of males and females in 2019 at USU does not elicit concern with the single outlier term results for males. Nevertheless, the consistent significant results realized by female student participants can provide a foundation of evidence to investigate whether curriculum components or their implementation produces the positive outcomes on female students.

First-time subgroup. After reflecting on the positive outcomes realized by the first-time subgroup population of students, which consists of students who entered USU as a Freshmen and have maintained continuous enrollments (see Appendix A), it made me wonder if SL should be included as a component of USU's first-year experience (FYE) curriculum. For many years USU has conducted FYEs, which has been a commonly accepted practice in higher education since the early 1900s used to introduce and orient students to the institutional culture and processes (Gordon, 1991). The experiences target incoming Freshmen with no prior enrollment in higher education and are intended to connect them with institutional values and resources. Like SL, a FYE is a recognized HIP. The outcomes slightly vary across institutions but the consensus, found in the literature, are positive in relation to persistence of participating students (Brownell & Swaner, 2010). At USU, SL courses are not part of the institution's first-year experience curriculum. However, after analyzing the First-Time student subgroups for this study, students entering USU as Freshmen, showed significant and positive persistence outcomes after participating in a SL course during Spring 2018. The effects size translates to 34 persisting students from Spring 2018 to Fall 2018 and a $77,248 retained. In a broader context, for a variety of reasons, USU retention from Spring to Fall terms has always presented a challenge, especially for Freshmen students progressing to their Sophomore year. Over the years at USU, the phrase *summer melt* has been coined to describe the annual attrition. However, based on the results of this study, programs like SL that are delivered during the Spring semesters merit further investigation to determine whether they should be included as part of a comprehensive retention strategy for first time Freshman students.

Notable institution-level characteristics. This study included analyzing student subgroups from both student-input and institutionally defined characteristics to discover interpretable insights. As the state's land grant institution, USU must provide access to its academic programming to urban and rural students across the state. Being true to its mission, USU delivers courses through various mediums of instruction, either in real-time through face-to-face or video broadcast (categorized as On-ground), virtual and asynchronous (Online), or a hybrid approach integrating real-time and virtual-asynchronous (Blended) classes. Methods for this analysis independently investigated groups of participating and control students who could be categorized into 10 institution-level characteristics (see Appendix A). After analyzing the combined lower- and upper-division course participants, four subgroups (Blended, 1-3 Terms, Full Time, and 4+ Terms) emerged with significant and interpretable results (see Figure 29).

Blended subgroup. In each term, student participants enrolled in Blended courses during the same term as the SL courses realized the greatest impacts of persistence with 2.02% of the students persisting to the next term. Similar results were found when independently analyzing term-base outcomes for students who took blended courses (see Figure 30). To be clear, this analysis does not look at SL-blended courses, rather participating students who were enrolled in

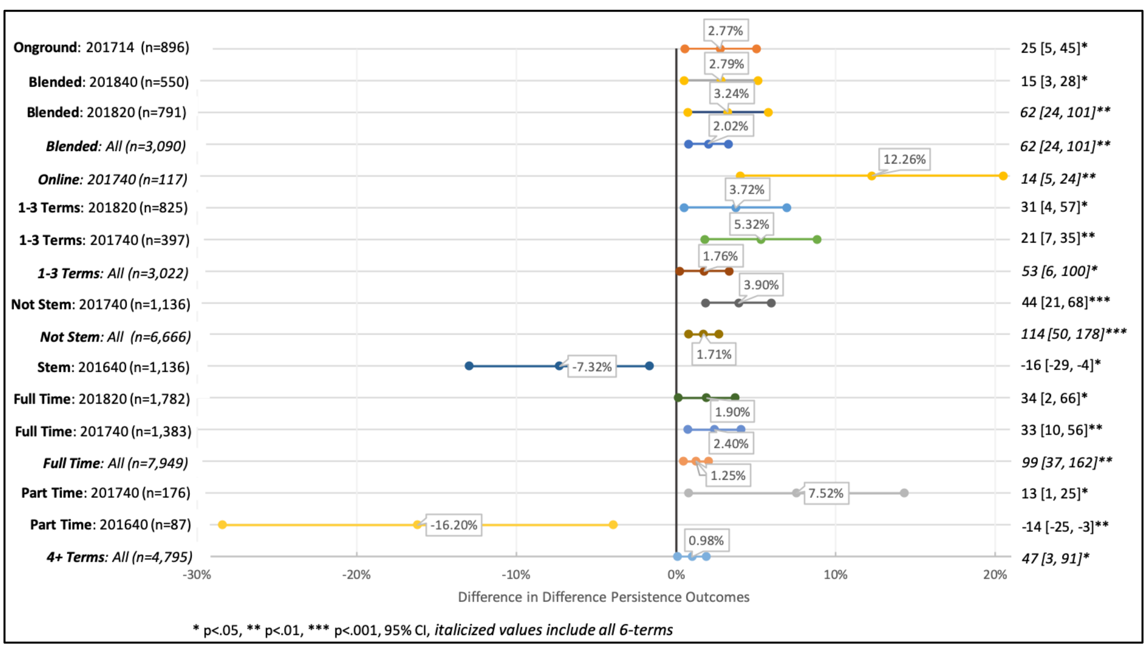

Figure 30. Subgroups of combined lower- and upper-division courses by terms and institutional characteristics.

blended courses during the same term. USU primarily uses a hybrid-model of blended courses to accommodate limited classroom space during the most desirable hours at its statewide campuses. The institutional motivation for blended course options is to optimize its business operations. Since 2014, when blended courses were identified in the institution's student information system, enrollments in these courses have more than doubled by 2019. As the institution continues to promote blended course offerings, programs with positive retention outcomes, like SL, should be considered when developing degree plans.

Research is increasing regarding HIPs and their effectiveness to produce expected outcomes along with various course delivery methods. Thompson (2018) provided a review of literature illustrating the multiple variations of SL course instruction from synchronous face-to-face and blended to fully online, placing emphasis on the lack of research in the creation and implementation of online-SL courses. This study is limited to the impacts of SL but provides information about students enrolled in online or blended courses. The categorical subgroup of Online students emerged with significant results during Fall 2017. Though significant, ($p < 0.01$) there were unfortunately only 117 students and results may be skewed due to lack of statistical power. Nevertheless, Figure 30 illustrates significant differences of persistence on students categorically separated by course delivery types.

1-3 terms subgroup. As previously addressed, Brownell and Swaner (2010) emphasized first-year programming as a strategic option for retaining freshman students. Results from this study show participants enrolled in 1-3 terms (freshman/sophomore) have realized beneficial student outcomes of persistence. One notable term, Fall 2017, realized a dramatic comparative difference of 5.32% of its students, retaining $47,712 for the institution the following term.

Full- and part-time subgroups. Research on why students leave college has identified lower continuity and term-to-term persistence outcomes for part-time students (Berkner et al., 2007; O'Toole et al., 2003). When categorically separating students as Full (taking 12 or more credits) or Part Time, this study shows significant overall and term-based results when comparing the subgroups. After analysis of the largest population of combined course divisions and across all terms, full time students emerged with a standardized effect of $449,856 of retained tuition over the 3 years of analysis. These results support other student success research on full-time enrollment benefits such as higher rates of retention and reduced time to graduation (Astin & Oseguera, 2012; Pascarella & Terrenzini, 2005). Unfortunately, only 11% of the analyzed SL students were categorized as part time, providing low statistical power for the analysis. Nevertheless, when part time students' data were independently analyzed, two terms produced significant and contrasting results. In Fall 2016 ($p < 0.01$), only 87 students were analyzed showing negative results (an average loss of 14 students); whereas scales were balanced during Fall 2017 ($p < 0.05$), with only 176 participating students producing positive results with 13 students were retained. These seemingly conflicting results are something that merits further investigation. The results for full and part time students in this study did not fully compliment similar work done by Astin and Oseguera, but it supported their full-time student research claims for Utah State University students.

STEM and not STEM subgroups. The last set of categorical subgroups included in the results of this study are to be interpreted as exploratory and should not be determined a priori. STEM and Not STEM subcategory results were a product of the statistical software used to perform the PPSM methods and may be used to support research in STEM-related fields. At USU, the SL curriculum has been implemented in various lower- and upper-division elective courses with students enrolled in either STEM or Not STEM majors. Of the analyzed student participants who took SL courses, 75% of them were categorized as Not STEM, providing substantial statistical power for analysis. The overall combined analysis of $n = 6,666$ resulted in a $p = 0.0005$ and a positive persistence outcome difference of 1.71%. Results of this group should be similarly to the White and Not Hispanic or Latino subgroup results due to its predominant number of categorical participants available for study. Positive results of the large subgroups at USU further promotes the generalizable outcomes of nation-wide research on the HIP of SL.

Lower-Division Course Students

Student subgroup populations were independently analyzed by combining only lower-division (1000- and 2000-level) courses of students. To discover more detailed differences in persistence outcomes, further analyses of the lower-division course students were categorically separated by subgroup populations and independently analyzed. For comparison, the same analytic process was repeated using upper-division (3000- and 4000-level) courses of students and respective subgroup populations.

When comparing persistence outcomes between combined lower- and upper-division students (see Figure 30) to only lower-division course students (see Figure 31), it is apparent that lower-division students swayed the overall results. The greatest contrast between subgroup results was realized by student participants who were either full time or had attended 4+ terms.

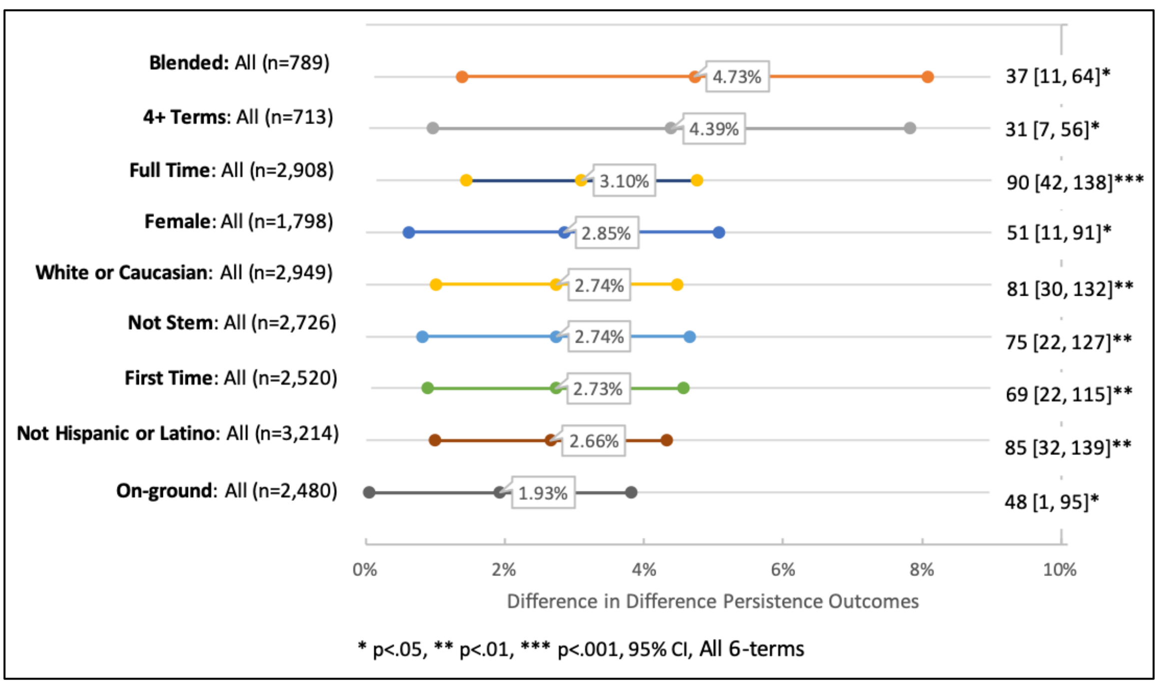

Figure 31. Subgroups of lower-division courses: All terms.

Interestingly, the lower-division students who had already completed 4+ terms and should have been in their Junior or Senior years, realized the greatest differential percentage of impact with a positive 4.39%, 3.41 percentage points higher than the combined term outcomes. This insight merits further investigation to better understand the impacts of following degree plans for students who have completed 4+ terms. What would be more interesting, would be understanding what types of activities, like SL, can correct a course of study to optimize persistence to graduation, and on which subgroups. The lower-division full-time subgroup of students also realized 1.25 percentage more than the combined terms. When using a practical unstandardized effect size of retained students to interpret the proportional comparison results, lower-divisions SL courses retained $198 per a 4+ term student, and $141 per full time student, whereas combined divisions were $45 and $57 per respective subgroups of students. These results build on the second research question that demonstrated that participation in lower-division SL courses retains a larger amount of tuition dollars than upper-division courses.

Subgroups of Upper-Division Course Students

An overall analysis of the upper-division courses produced results that were fraught with insignificant results and errors in the predictive model and were consequently not interpreted for this study. However, when Fall 2016, Spring 2017, and Spring 2018 terms were independently analyzed; Readmit, Female, and Not Stem subgroups of student data produced significant and interpretable results illustrated in Figure 32. Both Female and Not Stem STEM subgroups results are complimentary to results addressed earlier in this chapter. However, the Readmit student subgroup emerged with significant ($p = 0.0412$), yet cautiously interpreted, results because it is limited by statistical power with $n < 250$ and should be interpreted with caution.

Tinto's (1993) student success research produced a conceptual framework describing institutional activities and student behaviors contributing to students' departure from college. The

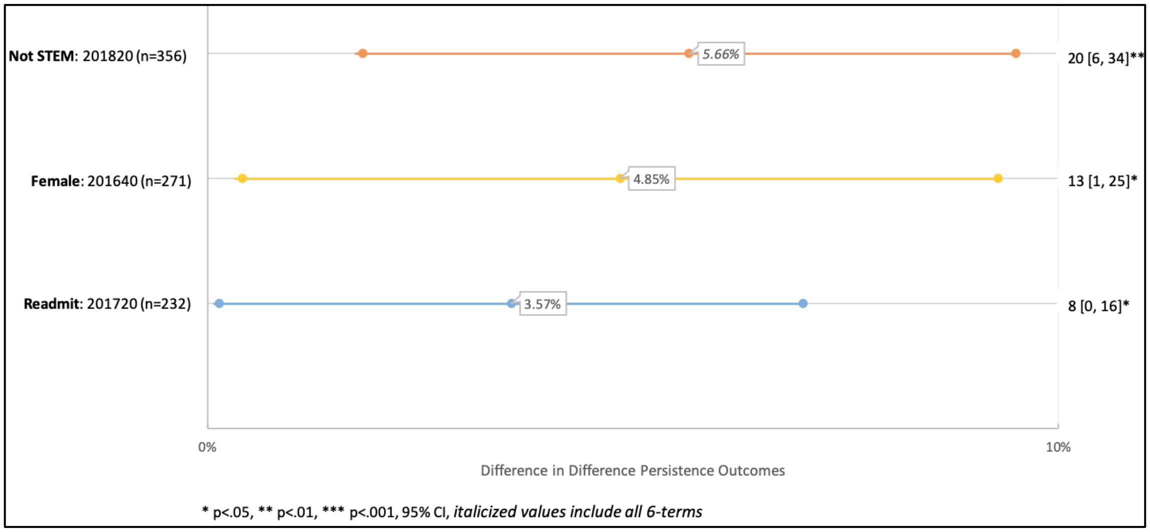

Figure 32. Subgroups of upper-division courses by terms.

holistic model accounted for individual attribute inputs that students bring with them to college. The model follows the inputs on a chronological path where they may account for attrition at any point of a student's life cycle. However, the model does not account for students who leave and transfer to another institution or drop out of college altogether (Tinto, 1993, 2012). The model also does not account for leave-of-absence (LOA) students who leave the university without filing a LOA and then return after reapplying to the institution.

Because of the model's (Tinto, 1993) shortcomings, a positive persistence outcome was discovered for Readmit students as one of the more interesting findings of this study. When upper-division course students were isolated and readmit subgroups of participating and control groups were compared, there were significant differences in term-to-term persistence between the groups of students. This means USU is losing students who, for whatever reason, have reinvested in their education and returned to the institution and then left again. Although there were a relatively small handful of the readmitted students who took a SL course during the Spring 2017 and persisted– unlike their statistically identical counterparts. These results merit further investigation and possible research on readmitted students to more fully understand what institutions can do to positively impact their rates of retention and persistence on to graduation.

Limitations

The limited variety of student demographics available for this analysis provided an atypical representation of higher education in America. The vast majority of students eligible for this analysis were ethnically more homogenous than the university student body: 91% of the SL participants were White which is 11 percentage points higher than the university during the timeframe of the analysis. Kuh et al. (2017) identified SL activities as an activity that has a predominantly higher proportion of ethnically diverse participants than any other HIP. However, USU does not have adequate diversity in its student body to support prior HIP research, and replicating this study at more ethnically diverse institution would be valuable.

The limited variety of student demographics available for this analysis provided an atypical representation of higher education in America. However, USU does not have adequate diversity in its student body to support prior HIP research; and replicating this study at more ethnically diverse institution would be valuable.

In addition, the study methods were designed to investigate the local impacts of SL on course participants compared to their local counterparts not taking SL courses. The SL curriculum is founded on the notion that community involvement provides authentic academic activities that benefit local services and are intentionally designed to engage students with peers, faculty, and community leaders. Utah has a unique culture of service guided by the predominant religious affiliation (The Church of Jesus Christ of Latter-day Saints) of its citizens (Colver, 2018) and most students raised in Utah have been actively participating in the HIP of SL as part of their religious activities, playing various roles as leaders or participants. Consequently, this local phenomenon may have diminished the comparison outcomes when participating and control students are already accustomed to this practice by reducing its high impact qualities. Reproducing this study across Utah and other American institutions of higher education, with a priori questions grounded in social and religious theory, could affect the design of future curriculum of community engagement learning programs.

Another study limitation, and a note of caution when replicating this study's methods, is interpreting the statistical results. The PPSM methods require relatively large numbers of students making up groups for comparison outcomes. Consequently, if there are large numbers of diverse eligible students these methods can provide hundreds of analyzed results with associated alphas and confidence intervals. The employed methods were designed to conduct statistical hypothesis testing. When multiple hypotheses are tested there is a greater likelihood of making a Type I error. Results from this study (see Appendices D, E, and F) provide 65 significant p values out of 560 independently analyzed hypothesis tests. According to Bonferroni (Shaffer, 1995), a shortcoming of traditional statistical models is the built-in likelihood of finding significance by chance alone. This study conducted 560 analyses, and according to Bonferroni there is a 99.9% chance that at least one result is significant at $\alpha = 0.05$, even if all of the other tests are not and may be misinterpreted resulting in a Type I error (Shaffer, 1995). For this study, attempts were made to reduce the probability of making a type I error by interpreting the significant results using $\alpha < 0.05$ with caution and placing a higher significance value on $\alpha \leq 0.01$ and $\alpha \leq 0.001$. However, final interpretation of results not only accounted for significance testing but also used assigned unstandardized effect sizes for each test. "Standardized effect size [measures] are degrees of experimental design, which are comparable across studies even with different sample sizes. Thus, reporting observed effect size, along with p values, allows readers as well as research evaluate the importance (and statistical significance) of results" (Nakagawa, 2004, p. 1045). Using $p \leq 0.01$ or smaller and interpretable unstandardized effect sizes relative to the institution measured is recommended when interpreting PPSM results measuring impacts of persistence to the next term. For this study, USU-specific tuition dollars were used as a standardized language that local educational administrators and public officers can use to inform decision making. A pre-determined tuition multiplier was used to estimate an annual amount that one undergraduate USU student provides the institution in retained tuition. Consequently, when interpreting impacts of students participating in SL courses, the outcome results of persistence were translated into a standardized effect of retained tuition dollars.

Future Research

When conceptualizing persistence and degree completion as a complex phenomenon, this study drew from theories of student success to examine the influence a HIP has on pre-determined groups of local university students. Accounting for a variety of influential characteristics of each student in the courses, the analytic methods were then able to hold those characteristics constant and isolate SL as the only differentiating variable. Results of the study affirms recent calls in the literature (Chen, 2007; Chickering, 1972; Goldrick-Rab et al., 2009; Kinzie & Kuh, 2017; Pike et al., 2003) to acknowledge an integration of conceptual perspectives to consider the impact of an activity on student persistence. Beyond that, with the results in this study, the hope is to contribute to a broader and more detailed research perspective investigating why the curriculum and instruction of SL has positive impacts on some groups of students and seems to have no significant impact on others.

Existing scholarly work at the intersection of understanding how locally designed and implemented HIPs can impact an institution's student body includes several methodological shortcomings, some of which were addressed in this study. Methodologically, the application of a commonly accepted practice of propensity score matching combined with a resource intensive and statistically advanced predictive modeling method, PPSM, can be used to examine the local impacts and better account for endogeneity bias (Kil, Derr, et al., 2017; Menaldo, 2011). The study's results show that SL not only impacts different divisions and subgroups of students, it also has differing impacts when comparing term-based outcome results. Thus, further investigations are needed to understand whether there were strategic or unintentional curriculum and design decisions that can be correlated with the outcomes.

Results from this study found compelling positive persistence outcomes for student participants in SL courses during the academic year of 2018. During that same year, a cohort of undergraduate students also displayed higher than normal rates of retention. Within that timeframe, the institution made administrative decisions regarding community engaged learning and established a greater focus on programming and other respective efforts designed to retain students. The term-based persistence and retention phenomenon experienced that year merits further organizational and curriculum research understanding whether correlations may exist between the overall institutional persistence and SL course participation.

Decisions of persistence are considered products of a longitudinal process across a student's lifecycle (Tinto, 1975, 1993), and research has shown influences through various constructs and experiences that produces the behavioral outcomes. Persistence after the first and second years of college has been an extensive topic of research for the past few decades. There were interesting positive results reported in this study about a subgroup of students who were readmitted to USU and attended a SL course during the Spring 2017 term. When compared to their counterparts, a significant number persisted into the following Fall term. There is an opportunity for further research on curricular and co-curricular activities that have differing influence on persistence based on the terms they are delivered. For example, does an SL course for readmit students have a greater impact when delivered Fall than Spring or vice versa?

One of the most compelling research opportunities that emerged from this study is a local gender-based phenomenon. Female student participants of USU SL courses persisted when compared to their non-SL female counterparts who did not participate; whereas, the male students did not. In fact, when compared to their gender counterparts, male students essentially displayed no difference in persistence whatsoever. The stark contrast of gender-based results sparks socio-cultural questions relative to Utah residents. Before pursuing the cultural investigations, it is recommended to reproduce this study at other prominent institutions across the state with a theory that female students will show positive outcomes whereas male students will not show any differences.

A key contribution of this study is its utility to investigate the local impacts of persistence on students. Prior student success research has resulted in the formation of high impact practices that were identified as curricular and co-curricular practices that positively influence student persistence and institutional rates of retention. HIPs are widely accepted, so much so, that student participation in HIPs are being mandated by political leaders and blindly implemented across institutions of higher education. It is dangerous to individual students and their academic success to assume that ubiquitous implementation will produce expected positive outcomes on all local and subgroup student populations. As such, it is highly recommended for each institution that designs and implements HIPs use the established protocols of this study to investigate the impacts on their local students who participate in curricular and co-curricular HIPs. By so doing, institutions can be more intentional when designing and redesigning curriculum and instruction through ongoing assessment and evaluation using accountability metrics that are tied back to their targeted populations of students.

Conclusion

The purpose of this study was to assess the impacts of persistence on students enrolled in qualified USU courses following the institution's standardized SL curriculum. The study research questions, and methods of analysis were designed to inform local academic stakeholders of the impacts their curricular decisions had on student success and persistence outcomes. The research outcomes complement prior student success research on HIPs and more specifically SL. Results demonstrate a positive return on investments, as measured by retained tuition, to local administrators who value community engaged learning programming for USU students.

Results from this study not only demonstrate the value for Utah students to participate in the HIP of SL, but a reproducible research methodology. For reasons described in this study, the application of the IEO model proved a useful guide that structured prior research. The model also contextualized the research methods which helped to interpret student outcome results. There are a wide variety of factors that contribute to student success outcomes in higher education, and this study demonstrated the use of PPSM to isolate the factors for analysis and is a contribution to the body of research literature. Guidance from the IEO model and use of the PPSM methods make it possible for institutions to investigate their available data to understand how they can iterate forward toward successful and effective programming.

For decades, our federal and state governing bodies have invested valuable resources to promote social mobility through access to new knowledge and attainment of marketable credentials, and “our students shouldn’t have to rely on luck to have transformative learning experiences” (Brownell & Swaner, 2010, p. 51). Consequently, public institutions have the responsibility to understand the impacts of curricular and co-curricular programming decisions upon its students. As such, it is incumbent upon these academic administrators to deploy HIPs, like SL, that deliver higher persistence and student success outcomes. Only when these *best practices* are supported by timely and localized research can they be truly declared *high impact* for their student body. The research methods used by this study are the means for administrators and stakeholders alike to make such assertions with fidelity and confidence.

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APPENDICES

Appendix A

Student Subgroup Categories and Definitions

Table A1

Student Subgroup Categories and Definitions

Student Group	Definition
0 Terms Completed	Students with 0 terms in their collegiate career completed; incoming freshmen
1-3 Terms Completed	Students who have completed 1 to 3 terms in their collegiate career
4+ Terms Completed	Students with 4 or more terms in their collegiate career completed
All On-Campus	Students attending all courses face-to-face
Online or Broadcast	Students attending all courses online or via broadcast
Mixed or Blended Course Modality	Students attending both face-to-face and online or broadcast courses
Full-time Students	Undergraduate students enrolled in 12 or more credits; Graduate students enrolled in 9 or more credits
Part-time Students	Undergraduate students enrolled in less than 12 credits; Graduate students enrolled in less than 9 credits
First Time in College	Students who enter USU as new freshmen, who have maintained continuous enrollment or records of absences (i.e. LOA)
Transfer Students	Students who attended another university prior to attending USU
Readmitted Students	Students who attended USU, left for a time (without filing a LOA), and return after re-applying to USU
Unknown Undergraduate Type	Students with an unknow admitted type
STEM	Students with a primary major that in science, technology, engineering, or mathematics
Non-STEM	Students with a primary major that is not in science, technology, engineering, or mathematics
Female	Students identifying as female
Male	Students identifying as male
Non-Hispanic or Latino	Students who do not identify as Hispanic or Latino
Hispanic or Latino	Students who identify as Hispanic or Latino
Race: Two or More	Students who identify with two or more races
Race: Unknown	Students who did not provided race information
Race: Asian	Students who identify as Asian
Race: Black or African American	Students who identify as African American
Race: Pacific Islander	Students who identify as a Pacific Islander
Race: American Indian/Alaskan Native	Students who identify as American Indian or Alaska Native
Race: White or Caucasian	Students who identify as White or Caucasian

Appendix B

USU Community Engaged Learning Course Designation Criteria

USU Community Engaged Learning Course Designation Criteria

The Community Engaged Learning (CEL) course approval form and syllabus should clearly demonstrate learning outcomes for community engagement and have a clear plan for course reflection.

Community-Engaged Learning (Service-Learning) is a teaching and learning strategy that integrates meaningful community engagement with instruction and reflection to enrich the learning experience, teach civic responsibility, and strengthen communities.

Reflection: A key component of Community-Engaged Learning is regular reflection, which connects the students' community-based experiences to the learning goals for the course. If your syllabus does not specifically address reflection, please attach documentation that demonstrates the role of this practice in your course. Examples of reflection include class discussions, journal entries, papers, videos, or presentations.

Please answer the following questions about the course:

Please select all fields into which this course falls:
First Year Connections
Orientation
General Education
Depth Requirement
Breadth Requirement
Requirement for Major
Elective
Internship/Practicum
Graduate Level Course

This Course is:
Proposed
Existing

Is the Community-Engaged Learning component of this course required?
Yes
No

Does your course have a minimum number of community engagement hours per student?
If so, how many?

Percent of final grade the Community-Engaged Learning component makes up:

This Course is:

Community-Engaged Learning Class - Every student in this section of the course is required to participate in the community-engaged learning experience. The SL designation refers to a particular section of a course with a particular instructor.

Community-Engaged Learning Option in Class - Students are given a choice by the instructor to participate in a community-engaged learning experience or some other equivalent assignment. The SL designation refers to a particular section of a course with a particular instructor.

Community-Engaged Learning Course – Every instructor teaching the course uses community-engaged learning pedagogy. In some cases, the department will create a standard syllabus for such courses. A Community-Engaged course can have a required or optional community-engaged learning experience.

Please check all Community-Engaged Learning Outcomes that your course will include. If these outcomes do not fully describe the learning outcomes for your course, please add your own. It is an expectation that all courses help to increase civic awareness, skills, and commitment. Additional resources can be provided by CCE for courses that don't inherently meet one of these outcomes.

This course includes the following Community-Engaged Learning Outcomes:

Civic Awareness - Demonstrate depth of thought and understanding of course material and how it applies to larger community.

Civic Skills - Demonstrates oral and written communication skills, critical thinking, initiative, time management, organization, leadership, self-awareness, problem solving, and other job/life skills.

Civic Action – Demonstrates responsibility towards the larger community through action

Other (please fill in):

Reflection: Please explain how you will use reflection to enhance learning:

Please indicate which community partner(s) you intend to work with and describe the project to be completed. If you have not yet confirmed your community partner, please indicate possibilities. Explain how this community engaged learning or research is addressing a real community need that has been identified by the community.

All Community-Engaged Learning designated courses must include the following Community-Engaged Learning definition on the course Syllabus:

Community Engaged Learning, or Service-Learning, is a teaching and learning strategy that integrates meaningful community service with instruction and reflection to enrich the learning experience, teach civic responsibility, and strengthen communities. As part of this course, students will be given the opportunity to apply course content to a real, community-identified need in a context of partnership and reciprocity.

Do you agree to include this definition in your syllabus?

Yes/No (please explain)

If no, please explain:

For Carnegie reporting purposes, the CCE utilizes AggieSync to capture student community engagement hours. Would you be willing to have your students log their community engagement hours in AggieSync?

Yes

No (please explain)

If no, how are you capturing hours and impact?

Please certify you have attached your course syllabus below

Yes, I have attached my course syllabus below

Appendix C

Analytics System and Methods Patent

Weblink to the full patent application:
https://patentimages.storage.googleapis.com/47/18/1c/97570e04a5e366/US20170256172A1.pdf

US 20170256172A1

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(43) **Pub. Date: Sep. 7, 2017**

(54) **STUDENT DATA-TO-INSIGHT-TO-ACTION-TO-LEARNING ANALYTICS SYSTEM AND METHOD**

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(21) Appl. No.: **15/451,147**

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(57) **ABSTRACT**

Student data-to-insight-to-action-to-learning analytics system and method use an evidence-based action knowledge database to compute student success predictions, student engagement predictions, and student impact predictions to interventions. The evidence-based action knowledge database is updated by executing a multi-tier impact analysis on impact results of applied interventions. The multi-tier impact analysis includes using changes in key performance indicators (KPIs) for pilot students after each applied intervention and dynamic matching of the pilot students exposed to the appropriate interventions to other students who were not exposed to the appropriate interventions.

	Engagement rules				**KPIs for automated efficacy analysis**				
Rule ID	**Rule attribute**	**Operator**	**Operand**	**Set function**	**KPI rule attribute**	**Operator**	**Operand**	**Set function**	**Duration**
100	Consistency score	<	50	&	Consistency score Δ	>	20	or	5 days
	2 weeks from exam	eq	TRUE	&	Delta grade	>	0.5		3 weeks
	Course = gatekeeper	eq	TRUE	&					
	Prediction score	in	VL, L						
101	ST GPA mid-term – LT STEM GPA	<	-1.3	&	Attendance in math tutoring	eq	TRUE	or	3 days
	Prior STEM GPA	>	3.2	&	STEM grade change	>	0.5		1 week
	Activity level bucket	eq	high	&					
	Prediction score	in	VL, L						
102	Major = accounting	eq	TRUE	&	Attendance in English tutoring	eq	TRUE	or	3 days
	Course = English composition	eq	TRUE	&	Increase in LMS activity velocity	>	20%		1 week
	Grade prediction	in	VL, L, M						

Appendix D

Question 1 Table

Table D1

Overall Summary for Combined Lower and Upper Division Courses

		Participant Group		Control Group					
Term	Matched Participants	Outcome *Predicted*	Outcome *Actual*	Outcome *Predicted*	Outcome *Actual*	Outcome Diff.	*p* value	CI	Persisted
201620	1,092	0.8754	0.9102	0.8754	0.8791	0.0131	0.2718	0.0233	14 [-11, 40]
201640	963	0.8999	0.8892	0.8999	0.9091	-0.0199	0.134	0.26	-19 [-44, 6]
201720	1,588	0.8655	0.8877	0.8656	0.8748	0.013	0.225	0.021	21 [-13, 54]
201740	1,564	0.8961	0.9474	0.8962	0.9176	0.0299	0.0006***	0.017	47 [20, 73]
201820	2,030	0.8704	0.903	0.8704	0.8843	0.0187	0.0415*	0.018	38 [1, 75]
201840	1,697	0.9125	0.9521	0.9125	0.9406	0.0115	0.1277	0.0148	20 [-6, 45]
Overall	8,948	0.8858	0.9167	0.8858	0.9033	0.0134	0.0009***	0.008	120 [48,91]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Appendix E

Question 2 Tables

Table E1

Lower Division Courses

		Participant group		Control group					
Term	Matched participants	Outcome *predicted*	Outcome *actual*	Outcome *predicted*	Outcome *actual*	Outcome diff.	*p* value	CI	Persisted
201620	390	0.8205	0.8407	0.8204	0.794	0.0465	0.0775	0.0516	18 [-2, 38]
201640	563	0.8831	0.8693	0.8834	0.8794	-0.0099	0.0597	0.0367	-6 [-26, 15]
201720	552	0.8105	0.8084	0.8103	0.7764	0.0318	0.1663	0.045	18 [-7, 42]
201740	513	0.8721	0.9005	0.8726	0.8735	0.0275	0.1537	0.0378	14 [-5, 33]
201820	643	0.8167	0.8405	0.8158	0.792	0.0476	0.0213*	0.0405	31 [5, 57]
201840	615	0.8911	0.9093	0.8914	0.8922	0.0175	0.2913	0.0324	11 [-9, 31]
Overall	3,290	0.8502	0.8623	0.8501	0.8362	0.0261	0.0019**	0.0164	86 [32, 140]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table E2

Upper Division Courses

		Participant group		Control group					
Term	Matched participants	Outcome *predicted*	Outcome *actual*	Outcome *predicted*	Outcome *actual*	Outcome diff.	*p* value	CI	Persisted
201620	640	0.9145	0.9458	0.917	0.9564	-0.008	0.5	0.0233	-5 [-20, 10]
201640	500	0.9217	0.9201	0.9229	0.8968	0.0245	0.1746	0.0355	12 [-6, 30]
201720	908	0.9112	0.9521	0.9128	0.9449	0.0089	0.3738	0.0196	8 [-10, 26]
201740	943	0.912	0.9668	0.9129	0.9599	0.0077	0.3675	0.0169	7 [-9, 23]
201820	1,106	0.9134	0.9387	0.9156	0.9541	-0.0132	0.1526	0.0181	-15 [-35, 5]
201840	924	0.9236	0.9652	0.9237	0.9698	-0.0044	0.5849	0.016	-4 [-19, 11]
Overall	5,024	0.9156	0.9503	0.917	0.951	0.0008	0.8575	0.0083	4 [-38, 46]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Appendix F

Question 21 Tables

Table F1.1

Combined Lower and Upper Division Courses: All Terms

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	8,926	0.8864	0.9178	0.8865	0.9044	0.0135	0.0009***	0.0079	121 [50, 191]
Completed Terms: 0 Terms	1,077	0.8399	0.8735	0.8402	0.8572	0.0166	0.2388	0.0276	18 [-12, 48]
Completed Terms: 1-3 Terms	3,022	0.8601	0.8805	0.8687	0.8714	0.0176	0.0253*	0.0155	53 [6, 100]
Completed Terms: 4+ Terms	4,795	0.9126	0.9497	0.9074	0.9347	0.0098	0.0358*	0.0091	47 [3, 91]
Course Modality: All On-Ground	5,491	0.8869	0.9083	0.8869	0.9013	0.007	0.1831	0.0103	38 [-18, 95]
Course Modality: All Online	364	0.7628	0.8534	0.763	0.8014	0.0522	0.0557	0.0535	19 [0, 38]
Course Modality: Mixed or Blended	3,090	0.8984	0.9391	0.8985	0.9189	0.0202	0.0014**	0.0124	62 [24, 101]
Ethnicity: Hispanic or Latino	276	0.8878	0.9199	0.882	0.8983	0.0157	0.5025	0.0461	4 [-8, 17]
Ethnicity: Not Hispanic or Latino	8,666	0.8857	0.9166	0.8859	0.9035	0.0134	0.0012**	0.0081	116 [46, 186]
Full-time vs. Part-time: Full-time	7,949	0.8992	0.9302	0.9026	0.9211	0.0125	0.0018**	0.0079	99 [37, 162]
Full-time vs. Part-time: Part-time	982	0.7785	0.8087	0.7774	0.7882	0.0195	0.2429	0.0327	19 [-13, 51]
Gender: Female	5,030	0.8878	0.9212	0.8886	0.9035	0.0184	0.0007***	0.0106	93 [39, 46]
Gender: Male	3,915	0.8832	0.9111	0.8825	0.9032	0.0073	0.2353	0.0121	29 [-19, 76]
Race: American Indian/Alaskan Native	40	0.8552	0.8618	0.8291	0.7683	0.0675	0.276	0.1223	3 [-2, 8]
Race: Asian	157	0.8652	0.9237	0.8868	0.9344	0.0109	0.6984	0.0555	2 [-7, 10]
Race: Black or African American	108	0.8278	0.7926	0.8496	0.8634	-0.049	0.3261	0.0982	-5 [-16, 5]
Race: Pacific Islander	35	0.8652	0.8842	0.8546	0.8736	0	0.9995	0.1403	0 [-5, 5]
Race: Two or More	229	0.8808	0.9323	0.8779	0.9131	0.0162	0.4823	0.0454	4 [-7, 14]
Race: Unknown	223	0.8495	0.8815	0.8639	0.8768	0.0191	0.5222	0.0587	4 [-9, 17]
Race: White or Caucasian	8,149	0.8883	0.9192	0.8878	0.9053	0.0133	0.0016**	0.0083	108 [41, 176]
STEM Major: Not STEM	6,666	0.8802	0.9121	0.8813	0.8961	0.0171	0.0005***	0.0096	114 [50, 178]
STEM Major: STEM	2,255	0.9049	0.9349	0.8999	0.9264	0.0035	0.624	0.014	8 [-24, 39]
Undergraduate Type: First Time in College	4,905	0.8837	0.9092	0.8877	0.9043	0.0089	0.1099	0.0109	44 [-10, 97]
Undergraduate Type: Readmit	1,830	0.8965	0.924	0.8923	0.9099	0.0098	0.2466	0.0167	18 [-13, 48]
Undergraduate Type: Transfer	2,153	0.8847	0.933	0.8783	0.8996	0.0269	0.0013**	0.0164	58 [23, 93]
Undergraduate Type: Unknown Undergraduate Type	10	0.7079	0.6934	0.801	0.8266	-0.0401	0.7824	0.3016	0 [-3, 3]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F1.2

Combined Lower and Upper Division Courses – 201620

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	1,089	0.8757	0.9103	0.8758	0.897	0.0133	0.2627	0.0234	14 [-11, 40]
Completed Terms: 0 Terms	34	0.714	0.7471	0.7223	0.8204	-0.0649	0.4522	0.1714	-2 [-8, 4]
Completed Terms: 1-3 Terms	402	0.8388	0.8572	0.8461	0.8549	0.0096	0.664	0.1714	4 [-65, 73]
Completed Terms: 4+ Terms	651	0.9073	0.9523	0.9068	0.9333	0.0185	0.1627	0.0259	12 [-5, 29]
Course Modality: All On-Ground	708	0.8703	0.8983	0.8704	0.8971	0.0013	0.933	0.0293	1 [-20, 22]
Course Modality: Mixed or Blended	374	0.8852	0.933	0.8851	0.8967	0.0363	0.0645	0.0385	14 [-1, 28]
Ethnicity: Hispanic or Latino	49	0.8744	0.916	0.8678	0.8622	0.0472	0.4695	0.1293	2 [-4, 9]
Ethnicity: Not Hispanic or Latino	1,041	0.8754	0.9098	0.8757	0.8986	0.0115	0.3412	0.0237	12 [-13, 37]
Full-time vs. Part-time: Full-time	980	0.8862	0.9244	0.8915	0.9133	0.0164	0.1647	0.0231	16 [-7, 39]
Full-time vs. Part-time: Part-time	110	0.7787	0.7815	0.7723	0.7925	-0.0175	0.7256	0.0979	-2 [-13, 9]
Gender: Female	617	0.8786	0.9281	0.8795	0.8941	0.035	0.0253*	0.0307	22 [3, 41]
Gender: Male	467	0.8711	0.8868	0.871	0.9002	-0.0135	0.4671	0.0363	-6 [-23, 11]
Race: American Indian/Alaskan Native	8	0.8331	0.7308	0.7598	0.6401	0.0174	0.9291	0.4288	0 [-3, 4]
Race: Asian	15	0.8436	0.8835	0.8682	0.9766	-0.0685	0.2147	0.1107	-1 [-3, 1]
Race: Black or African American	16	0.8058	0.9172	0.8139	0.8373	0.088	0.5371	0.3013	1 [-3, 6]
Race: Pacific Islander	3	0.8774	1	0.8214	0.7226	0.2214	0.5075	2.6429	1 [-7, 9]
Race: Two or More	24	0.8302	0.9174	0.8746	0.921	0.0408	0.56	0.1397	1 [-2, 4]
Race: Unknown	17	0.8721	0.9039	0.8465	0.807	0.0713	0.4996	0.2117	1 [-2, 5]
Race: White or Caucasian	1,003	0.8788	0.9123	0.8777	0.9006	0.0107	0.3868	0.0242	11 [-14, 35]
STEM Major: Not STEM	807	0.8718	0.912	0.8721	0.8864	0.0259	0.0682	0.0278	21 [-2, 43]
STEM Major: STEM	273	0.8867	0.9052	0.8842	0.922	-0.0193	0.3876	0.0438	-5 [-17, 7]
Undergraduate Type: First Time in College	599	0.8557	0.89	0.8652	0.888	0.0115	0.4962	0.0331	7 [-13, 27]
Undergraduate Type: Readmit	236	0.8997	0.9305	0.8959	0.9117	0.0151	0.5149	0.0454	4 [-7, 14]
Undergraduate Type: Transfer	247	0.8998	0.9386	0.8788	0.9025	0.0152	0.5299	0.0474	4 [-8, 15]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F1.3

Combined Lower and Upper Division Courses – 201640

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	960	0.9008	0.8902	0.9009	0.9098	-0.0196	0.138	0.026	-19 [-44, 6]
Completed Terms: 0 Terms	228	0.8741	0.8808	0.8766	0.9001	-0.0168	0.5483	0.055	-4 [-16, 9]
Completed Terms: 1-3 Terms	298	0.8923	0.8817	0.9028	0.906	-0.0139	0.5733	0.0483	-4 [-19, 10]
Completed Terms: 4+ Terms	435	0.9186	0.8986	0.9094	0.9151	-0.0257	0.176	0.0373	-11 [-27, 5]
Course Modality: All On-Ground	693	0.8992	0.8769	0.8993	0.9074	-0.0305	0.057	0.0314	-21 [-43, 1]
Course Modality: Mixed or Blended	269	0.9017	0.921	0.9017	0.9135	0.0075	0.7483	0.0457	2 [-10, 14]
Ethnicity: Hispanic or Latino	54	0.9055	0.8929	0.8978	0.8874	-0.0022	0.9707	0.1178	0 [-6, 6]
Ethnicity: Not Hispanic or Latino	906	0.8995	0.8887	0.9001	0.9099	-0.0206	0.1308	0.0268	-19 [-43, 6]
Full-time vs. Part-time: Full-time	875	0.9091	0.915	0.9136	0.9266	-0.0071	0.5785	0.0251	-6 [-28, 16]
Full-time vs. Part-time: Part-time	87	0.8068	0.6274	0.8026	0.7853	-0.162	0.0099**	0.1225	-14 [-25, -3]
Gender: Female	548	0.903	0.9161	0.9029	0.9081	0.008	0.6319	0.0327	4 [-14, 22]
Gender: Male	414	0.8958	0.854	0.8964	0.9103	-0.0557	0.0094**	0.042	-23 [-40, -6]
Race: American Indian/Alaskan Native	2	0.8378	1	0.9011	0.8672	0.1961	0.152	0.2896	0 [0, 1]
Race: Asian	16	0.9159	0.9163	0.91	0.9383	-0.028	0.7459	0.1749	0 [-3, 2]
Race: Black or African American	15	0.8921	0.7563	0.8936	0.8873	-0.1296	0.3718	0.3019	-2 [-6, 3]
Race: Pacific Islander	2	0.8677	1	0.9057	0.8879	0.1501	0.5206	0.8356	0 [-1, 2]
Race: Two or More	29	0.9126	0.9749	0.905	0.9304	0.0368	0.498	0.1085	1 [-2, 4]
Race: Unknown	15	0.9186	0.8756	0.8925	0.8971	-0.0477	0.642	0.2074	-1 [-4, 2]
Race: White or Caucasian	881	0.8993	0.8878	0.8998	0.9084	-0.0202	0.1464	0.0273	-18 [-42, 6]
STEM Major: Not STEM	741	0.8975	0.9033	0.8959	0.9054	-0.0039	0.796	0.0293	-3 [-25, 19]
STEM Major: STEM	220	0.912	0.8471	0.9127	0.921	-0.0732	0.0111*	0.0564	-16 [-29, -4]
Undergraduate Type: First Time in College	551	0.9022	0.8931	0.9012	0.9168	-0.0247	0.1443	0.0332	-14 [-32, 5]
Undergraduate Type: Readmit	189	0.8925	0.8451	0.8995	0.896	-0.044	0.1753	0.0637	-8 [-20, 4]
Undergraduate Type: Transfer	214	0.9061	0.923	0.9024	0.9049	0.0144	0.6015	0.0543	3 [-9, 15]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F1.4

Combined Lower and Upper Division Courses – 201720

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	1,580	0.8671	0.8893	0.8671	0.8773	0.012	0.2604	0.0209	19 [-14, 52]
Completed Terms: 0 Terms	78	0.6706	0.7551	0.6714	0.6534	0.1025	0.1405	0.1367	8 [-3, 19]
Completed Terms: 1-3 Terms	666	0.8407	0.8326	0.8433	0.8377	-0.0026	0.891	0.0376	-2 [-27, 23]
Completed Terms: 4+ Terms	830	0.9044	0.9454	0.9008	0.9235	0.0184	0.1098	0.0226	15 [-3, 34]
Course Modality: All On-Ground	973	0.8671	0.8911	0.8672	0.8735	0.0176	0.1935	0.0266	17 [-9, 43]
Course Modality: All Online	72	0.6366	0.7564	0.6366	0.6695	0.087	0.2401	0.1458	6 [-4, 17]
Course Modality: Mixed or Blended	538	0.8929	0.8991	0.893	0.9036	-0.0044	0.7941	0.0334	-2 [-20, 16]
Ethnicity: Hispanic or Latino	48	0.871	0.9118	0.8729	0.8955	0.0181	0.7282	0.1032	1 [-4, 6]
Ethnicity: Not Hispanic or Latino	1,536	0.8652	0.8868	0.8653	0.8739	0.013	0.2343	0.0214	20 [-13, 53]
Full-time vs. Part-time: Full-time	1,366	0.8833	0.8996	0.8875	0.8987	0.0049	0.6501	0.0212	7 [-22, 36]
Full-time vs. Part-time: Part-time	217	0.7585	0.8171	0.7474	0.7451	0.0609	0.0952	0.0716	13 [-2, 29]
Gender: Female	917	0.8691	0.8821	0.8658	0.8638	0.0151	0.3106	0.0291	14 [-13, 41]
Gender: Male	671	0.8605	0.8951	0.8653	0.8875	0.0124	0.4204	0.0301	8 [-12, 29]
Race: American Indian/Alaskan Native	8	0.8273	0.8492	0.8215	0.7482	0.0952	0.5569	0.3366	1 [-2, 3]
Race: Asian	36	0.8252	0.9263	0.8588	0.8932	0.0668	0.3783	0.1517	2 [-3, 8]
Race: Black or African American	23	0.6989	0.589	0.7779	0.8056	-0.1377	0.2936	0.2616	-3 [-9, 3]
Race: Pacific Islander	3	0.7861	0.638	0.8345	0.9428	-0.2564	0.2275	0.5149	-1 [-2, 1]
Race: Two or More	32	0.8411	0.9777	0.837	0.8824	0.0912	0.0864	0.1045	3 [0, 6]
Race: Unknown	30	0.7997	0.8112	0.8278	0.8614	-0.0221	0.8006	0.1747	-1 [-6, 5]
Race: White or Caucasian	1,452	0.8717	0.8921	0.869	0.876	0.0134	0.2278	0.0217	19 [-12, 51]
STEM Major: Not STEM	1,170	0.8604	0.8752	0.8613	0.8648	0.0113	0.3882	0.0256	13 [-17, 43]
STEM Major: STEM	407	0.8858	0.9293	0.8817	0.9097	0.0155	0.3821	0.0348	6 [-8, 20]
Undergraduate Type: First Time in College	846	0.8622	0.8634	0.8632	0.8699	-0.0056	0.7157	0.03	-5 [-30, 21]
Undergraduate Type: Readmit	303	0.8958	0.9434	0.8905	0.9048	0.0333	0.0866	0.0381	10 [-1, 22]
Undergraduate Type: Transfer	422	0.8568	0.9057	0.8527	0.8665	0.0351	0.102	0.0421	15 [-3, 33]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F1.5

Combined Lower and Upper Division Courses – 201740

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	1,562	0.8962	0.9473	0.8963	0.9182	0.0292	0.0007***	0.017	46 [19, 72]
Completed Terms: 0 Terms	266	0.8809	0.9184	0.8803	0.8844	0.0334	0.1901	0.05	9 [-4, 22]
Completed Terms: 1-3 Terms	397	0.8771	0.9348	0.8889	0.8934	0.0532	0.0031**	0.0352	21 [7, 35]
Completed Terms: 4+ Terms	893	0.9093	0.9617	0.9053	0.9413	0.0164	0.1051	0.0198	15 [-3, 32]
Course Modality: All On-Ground	896	0.9056	0.944	0.9056	0.9162	0.0277	0.0152*	0.0224	25 [5, 45]
Course Modality: All Online	117	0.8055	0.9416	0.8058	0.8193	0.1226	0.0037**	0.0824	14 [5, 24]
Course Modality: Mixed or Blended	549	0.9001	0.9541	0.9002	0.9406	0.0137	0.3037	0.0261	8 [-7, 22]
Ethnicity: Hispanic or Latino	37	0.8882	0.9709	0.8909	0.9195	0.0542	0.2571	0.0951	2 [-2, 6]
Ethnicity: Not Hispanic or Latino	1,527	0.8963	0.9468	0.8963	0.9175	0.0293	0.0009***	0.0173	45 [18, 71]
Full-time vs. Part-time: Full-time	1,383	0.91	0.9547	0.914	0.9348	0.024	0.005**	0.0167	33 [10, 56]
Full-time vs. Part-time: Part-time	176	0.7899	0.8909	0.7835	0.8094	0.0752	0.0296*	0.0677	13 [1, 25]
Gender: Female	851	0.8916	0.9529	0.895	0.9245	0.0318	0.0047**	0.022	27 [8, 46]
Gender: Male	709	0.9016	0.9405	0.8978	0.9085	0.0282	0.0372*	0.0265	20 [1, 39]
Race: American Indian/Alaskan Native	4	0.8536	1	0.8547	0.7695	0.2316	0.0349*	0.2132	1 [0, 2]
Race: Asian	21	0.8804	1	0.8887	0.9073	0.1009	0.1273	0.1319	2 [-1, 5]
Race: Black or African American	19	0.8886	0.9205	0.8905	0.9176	0.0049	0.9545	0.1756	0 [-3, 3]
Race: Pacific Islander	12	0.8759	0.8706	0.8416	0.7403	0.096	0.6751	0.6376	1 [-6, 9]
Race: Two or More	40	0.8973	0.9424	0.89	0.8945	0.0405	0.4562	0.1077	2 [-3, 6]
Race: Unknown	46	0.8792	0.9535	0.8806	0.8656	0.0893	0.1411	0.1197	4 [-1, 10]
Race: White or Caucasian	1,412	0.8972	0.9473	0.8977	0.9219	0.0259	0.004**	0.0176	37 [12, 61]
STEM Major: Not STEM	1,136	0.8882	0.9452	0.8908	0.9087	0.039	0.0002***	0.0205	44 [21, 68]
STEM Major: STEM	411	0.9187	0.9534	0.9132	0.9474	0.0006	0.9691	0.0285	0 [-11, 12]
Undergraduate Type: First Time in College	785	0.9012	0.9371	0.9025	0.9251	0.0132	0.2716	0.0235	10 [-8, 29]
Undergraduate Type: Readmit	352	0.8933	0.9422	0.8846	0.898	0.0355	0.0668	0.0379	12 [-1, 26]
Undergraduate Type: Transfer	416	0.89	0.97	0.8946	0.9212	0.0534	0.0015**	0.0328	22 [9, 36]
Undergraduate Type: Unknown Undergraduate Type	2	0.7468	1	0.8011	0.9885	0.0657	0.5357	0.3024	0 [0, 1]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F1.6

Combined Lower and Upper Division Courses – 201820

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	2,023	0.8712	0.9042	0.8711	0.8852	0.0189	0.0393*	0.018	38 [2, 75]
Completed Terms: 0 Terms	165	0.7524	0.8251	0.7509	0.7723	0.0512	0.2319	0.0841	8 [-5, 22]
Completed Terms: 1-3 Terms	825	0.8395	0.8712	0.85	0.8445	0.0372	0.0239*	0.0323	31 [4, 57]
Completed Terms: 4+ Terms	1,036	0.9139	0.9409	0.9033	0.9303	0.0001	0.9952	0.0203	0 [-21, 21]
Course Modality: All On-Ground	1,086	0.8602	0.8869	0.8602	0.8751	0.0117	0.3671	0.0255	13 [-15, 40]
Course Modality: All Online	145	0.7765	0.8145	0.7766	0.8205	-0.006	0.8933	0.0876	-1 [-14, 12]
Course Modality: Mixed or Blended	791	0.9013	0.9409	0.9013	0.9086	0.0324	0.0115*	0.0251	26 [6, 45]
Ethnicity: Hispanic or Latino	48	0.8726	0.9021	0.8783	0.9055	0.0022	0.9695	0.1161	0 [-5, 6]
Ethnicity: Not Hispanic or Latino	1,982	0.8703	0.903	0.8701	0.8837	0.0191	0.0399*	0.0182	38 [2, 74]
Full-time vs. Part-time: Full-time	1,782	0.8862	0.9196	0.8876	0.902	0.019	0.0387*	0.018	34 [2, 66]
Full-time vs. Part-time: Part-time	236	0.7499	0.7761	0.7686	0.7794	0.0153	0.6577	0.0679	4 [-12, 20]
Gender: Female	1,172	0.8764	0.9028	0.8785	0.886	0.0188	0.1239	0.024	22 [-6, 50]
Gender: Male	855	0.8622	0.9034	0.8605	0.882	0.0197	0.1542	0.0272	17 [-6, 40]
Race: American Indian/Alaskan Native	11	0.8925	0.9231	0.7872	0.7108	0.1069	0.3267	0.2188	1 [-1, 4]
Race: Asian	27	0.8656	0.9091	0.8687	0.9034	0.0088	0.8966	0.1357	0 [-3, 4]
Race: Black or African American	18	0.829	0.7303	0.8335	0.8874	-0.1526	0.231	0.2545	-3 [-7, 2]
Race: Pacific Islander	7	0.8208	0.8673	0.8368	0.8973	-0.014	0.9111	0.2709	0 [-2, 2]
Race: Two or More	47	0.8729	0.8629	0.8637	0.9154	-0.0617	0.2876	0.1145	-3 [-8, 2]
Race: Unknown	72	0.8222	0.8675	0.8463	0.9019	-0.0104	0.8434	0.1036	-1 [-8, 7]
Race: White or Caucasian	1,841	0.8729	0.9073	0.8734	0.8853	0.0225	0.0185*	0.0187	41 [7, 76]
STEM Major: Not STEM	1,567	0.865	0.8922	0.8666	0.8766	0.0172	0.118	0.0215	27 [-7, 61]
STEM Major: STEM	456	0.8925	0.9457	0.8831	0.9079	0.0284	0.0759	0.0314	13 [-1, 27]
Undergraduate Type: First Time in College	1,102	0.8647	0.9025	0.8735	0.8809	0.0304	0.0165*	0.0249	34 [6, 61]
Undergraduate Type: Readmit	402	0.8934	0.8944	0.8823	0.9058	-0.0225	0.237	0.0374	-9 [-24, 6]
Undergraduate Type: Transfer	510	0.8692	0.9177	0.8562	0.8777	0.027	0.146	0.0363	14 [-5, 32]
Undergraduate Type: Unknown Undergraduate Type	3	0.6493	0.5738	0.7983	0.6043	0.1184	0.6709	0.6939	0 [-2, 2]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F1.7

Combined Lower and Upper Division Courses – 201840

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	1,693	0.9126	0.9542	0.9126	0.9416	0.0126	0.0924	0.0147	21 [-4, 46]
Completed Terms: 0 Terms	303	0.8849	0.9011	0.8847	0.9049	-0.004	0.8669	0.0464	-1 [-15, 13]
Completed Terms: 1-3 Terms	434	0.9108	0.9421	0.9158	0.9343	0.0128	0.4029	0.0301	6 [-8, 19]
Completed Terms: 4+ Terms	947	0.9222	0.973	0.9202	0.9562	0.0148	0.0812	0.0167	14 [-2, 30]
Course Modality: All On-Ground	1,115	0.9181	0.942	0.9181	0.938	0.004	0.6814	0.0191	4 [-17, 26]
Course Modality: All Online	28	0.8337	0.9376	0.8349	0.9517	-0.0129	0.8245	0.116	0 [-4, 3]
Course Modality: Mixed or Blended	550	0.9053	0.9732	0.9054	0.9454	0.0279	0.0177*	0.0231	15 [3, 28]
Ethnicity: Hispanic or Latino	36	0.918	0.9436	0.892	0.9246	-0.007	0.8989	0.1104	0 [-4, 4]
Ethnicity: Not Hispanic or Latino	1,660	0.9124	0.9524	0.9129	0.9409	0.012	0.1174	0.015	20 [-5, 45]
Full-time vs. Part-time: Full-time	1,543	0.9213	0.96	0.9237	0.9524	0.0101	0.1649	0.0142	16 [-6, 37]
Full-time vs. Part-time: Part-time	150	0.8218	0.8695	0.8154	0.838	0.0251	0.5211	0.077	4 [-8, 15]
Gender: Female	910	0.9148	0.9524	0.9123	0.9433	0.0066	0.5156	0.0199	6 [-12, 24]
Gender: Male	778	0.9098	0.9518	0.9128	0.9373	0.0175	0.1223	0.0222	14 [-4, 31]
Race: American Indian/Alaskan Native	2	0.9505	1	0.8661	0.8581	0.0575	0.4758	0.1662	0 [0, 0]
Race: Asian	36	0.885	0.9036	0.9215	0.9876	-0.0475	0.3588	0.1028	-2 [-5, 2]
Race: Black or African American	14	0.9148	0.9422	0.9024	0.8742	0.0556	0.5389	0.1823	1 [-2, 3]
Race: Pacific Islander	5	0.9411	1	0.9266	1	-0.0145	0.727	0.1082	0 [-1, 0]
Race: Two or More	50	0.9059	0.9465	0.9113	0.9432	0.0087	0.8469	0.0895	0 [-4, 5]
Race: Unknown	35	0.8746	0.8626	0.899	0.8979	-0.0109	0.879	0.1426	0 [-5, 5]
Race: White or Caucasian	1,544	0.9142	0.9554	0.9134	0.9427	0.012	0.1239	0.0152	19 [-5, 42]
STEM Major: Not STEM	1,224	0.9062	0.9471	0.9061	0.9375	0.0095	0.3064	0.0183	12 [-11, 34]
STEM Major: STEM	468	0.9293	0.9725	0.929	0.9521	0.0201	0.0858	0.0229	9 [-1, 20]
Undergraduate Type: First Time in College	1,004	0.916	0.9539	0.916	0.9422	0.0116	0.2291	0.0189	12 [-7, 31]
Undergraduate Type: Readmit	338	0.9044	0.9622	0.9085	0.9399	0.0264	0.1049	0.0319	9 [-2, 20]
Undergraduate Type: Transfer	339	0.9116	0.9467	0.9075	0.9405	0.0022	0.9003	0.0338	1 [-11, 12]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F2.1

Lower Division Courses – All Terms

Subgroup	Matched participants	Participant group Outcome predicted	Participant group Outcome actual	Control group Outcome predicted	Control group Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	3,290	0.8502	0.8623	0.8501	0.8362	0.0261	0.0019**	0.0164	86 [32, 140]
Completed Terms: 0 Terms	967	0.854	0.876	0.8536	0.8673	0.0084	0.5614	0.0283	8 [-19, 35]
Completed Terms: 1-3 Terms	1,608	0.8384	0.836	0.8455	0.8149	0.0282	0.0249*	0.0246	45 [6, 85]
Completed Terms: 4+ Terms	713	0.8718	0.9027	0.8565	0.8435	0.0439	0.0122*	0.0343	31 [7, 56]
Course Modality: All On-Ground	2,480	0.8499	0.8574	0.8501	0.8382	0.0193	0.045*	0.0189	48 [1, 95]
Course Modality: All Online	20	0.7229	0.6657	0.7233	0.6328	0.0333	0.8097	0.2777	1 [-5, 6]
Course Modality: Mixed or Blended	789	0.8544	0.8827	0.8538	0.8349	0.0473	0.0057**	0.0335	37 [11, 64]
Ethnicity: Hispanic or Latino	73	0.8287	0.8142	0.8078	0.7839	0.0094	0.893	0.1383	1 [-9, 11]
Ethnicity: Not Hispanic or Latino	3,214	0.8507	0.8634	0.8508	0.8369	0.0266	0.0017**	0.0166	85 [32, 139]
Full-time vs. Part-time: Full-time	2,908	0.8677	0.8864	0.871	0.8587	0.031	0.0002***	0.0166	90 [42, 138]
Full-time vs. Part-time: Part-time	374	0.7172	0.6824	0.7256	0.7014	-0.0105	0.7395	0.0618	-4 [-27, 19]
Gender: Female	1,798	0.8623	0.8714	0.8567	0.8373	0.0285	0.0122*	0.0223	51 [11, 91]
Gender: Male	1,491	0.8356	0.8514	0.843	0.835	0.0238	0.0553	0.0244	35 [-1, 72]
Race: American Indian/Alaskan Native	14	0.7663	0.6487	0.82	0.7657	-0.0634	0.548	0.2145	-1 [-4, 2]
Race: Asian	50	0.8388	0.8802	0.8494	0.8564	0.0344	0.6067	0.1322	2 [-5, 8]
Race: Black or African American	46	0.8196	0.7429	0.8298	0.8173	-0.0642	0.4488	0.1679	-3 [-11, 5]
Race: Pacific Islander	18	0.8442	0.8291	0.8359	0.8199	0.0009	0.9949	0.2845	0 [-5, 5]
Race: Two or More	98	0.8502	0.908	0.8422	0.8451	0.0549	0.1891	0.0821	5 [-3, 13]
Race: Unknown	106	0.8413	0.8223	0.8404	0.8299	-0.0085	0.8694	0.1015	-1 [-12, 10]
Race: White or Caucasian	2,949	0.8516	0.8647	0.8516	0.8374	0.0274	0.002**	0.0173	81 [30, 132]
STEM Major: Not STEM	2,726	0.8496	0.8594	0.8414	0.8238	0.0274	0.0051**	0.0192	75 [22, 127]
STEM Major: STEM	562	0.8529	0.8761	0.8732	0.8688	0.0276	0.1036	0.0332	16 [-3, 34]
Undergraduate Type: First Time in College	2,520	0.8531	0.8655	0.8592	0.8442	0.0273	0.0036**	0.0184	69 [22, 115]
Undergraduate Type: Readmit	372	0.831	0.8632	0.822	0.8066	0.0477	0.0742	0.0524	18 [-2, 37]
Undergraduate Type: Transfer	394	0.8506	0.8434	0.8198	0.8134	-0.0008	0.9756	0.0502	0 [-20, 19]
Undergraduate Type: Unknown Undergraduate Type	3	0.7548	0.6797	0.7744	0.6797	0.0196	0.959	1.9118	0 [-6, 6]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F2.2

Lower Division Courses – 201620

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	390	0.8205	0.8407	0.8204	0.794	0.0465	0.0775	0.0516	18 [-2, 38]
Completed Terms: 0 Terms	28	0.7155	0.767	0.6991	0.7225	0.0282	0.7899	0.2109	1 [-5, 7]
Completed Terms: 1-3 Terms	218	0.7992	0.7761	0.816	0.7858	0.0072	0.8441	0.0719	2 [-14, 17]
Completed Terms: 4+ Terms	143	0.8751	0.9548	0.8621	0.832	0.1098	0.006**	0.0779	16 [5, 27]
Course Modality: All On-Ground	265	0.8151	0.8181	0.8149	0.7795	0.0384	0.2324	0.0631	10 [-7, 27]
Course Modality: Mixed or Blended	121	0.8318	0.8899	0.8318	0.8251	0.0648	0.1543	0.0893	8 [-3, 19]
Ethnicity: Hispanic or Latino	19	0.8147	0.8192	0.7823	0.7993	-0.0126	0.9282	0.2852	0 [-6, 5]
Ethnicity: Not Hispanic or Latino	371	0.8209	0.8406	0.8217	0.7941	0.0474	0.0771	0.0525	18 [-2, 37]
Full-time vs. Part-time: Full-time	330	0.8386	0.8563	0.841	0.8245	0.0342	0.2093	0.0535	11 [-6, 29]
Full-time vs. Part-time: Part-time	58	0.7191	0.7626	0.7225	0.6482	0.1179	0.1403	0.1571	7 [-2, 16]
Gender: Female	221	0.8336	0.8611	0.8222	0.7875	0.0622	0.0794	0.0695	14 [-2, 29]
Gender: Male	169	0.8035	0.8135	0.8184	0.8011	0.0273	0.4906	0.0779	5 [-9, 18]
Race: American Indian/Alaskan Native	4	0.7269	0.7095	0.8322	0.8097	0.0051	0.9824	0.5897	0 [-2, 2]
Race: Asian	5	0.805	0.8973	0.8041	0.8858	0.0106	0.9512	0.5465	0 [-3, 3]
Race: Black or African American	9	0.7621	0.7725	0.7336	0.8261	-0.0821	0.7236	0.5109	-1 [-5, 4]
Race: Two or More	10	0.7954	0.7554	0.8136	0.863	-0.0894	0.5283	0.2909	-1 [-4, 2]
Race: Unknown	4	0.8049	0.8596	0.7687	0.6076	0.2158	0.342	0.4867	1 [-1, 3]
Race: White or Caucasian	350	0.8237	0.8443	0.8227	0.7941	0.0492	0.0747	0.0541	17 [-2, 36]
STEM Major: Not STEM	339	0.8248	0.8468	0.8061	0.768	0.0601	0.0507	0.0603	20 [0, 41]
STEM Major: STEM	50	0.7904	0.7873	0.8541	0.8541	-0.0031	0.9595	0.1226	0 [-6, 6]
Undergraduate Type: First Time in College	274	0.8149	0.8187	0.8243	0.7993	0.0288	0.3595	0.0617	8 [-9, 25]
Undergraduate Type: Readmit	61	0.8296	0.9394	0.8055	0.8086	0.1068	0.0702	0.1157	7 [-1, 14]
Undergraduate Type: Transfer	52	0.8392	0.8392	0.8169	0.7442	0.0727	0.3569	0.156	4 [-4, 12]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F2.3

Lower Division Courses – 201640

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	563	0.8831	0.8693	0.8834	0.8794	-0.0099	0.5975	0.0367	-6 [-26, 15]
Completed Terms: 0 Terms	276	0.8804	0.8904	0.8829	0.8885	0.0045	0.8608	0.0501	1 [-13, 15]
Completed Terms: 1-3 Terms	201	0.8846	0.8686	0.8893	0.8887	-0.0155	0.6084	0.0593	-3 [-15, 9]
Completed Terms: 4+ Terms	84	0.8884	0.7992	0.8713	0.8304	-0.0483	0.3957	0.1119	-4 [-13, 5]
Course Modality: All On-Ground	472	0.8828	0.864	0.8832	0.8759	-0.0114	0.5804	0.0404	-5 [-24, 14]
Course Modality: Mixed or Blended	91	0.8845	0.8959	0.884	0.9004	-0.005	0.91	0.0878	0 [-8, 8]
Ethnicity: Hispanic or Latino	22	0.8654	0.8103	0.8519	0.7592	0.0375	0.7737	0.2737	1 [-5, 7]
Ethnicity: Not Hispanic or Latino	541	0.8838	0.8718	0.8838	0.8811	-0.0093	0.6235	0.0372	-5 [-25, 15]
Full-time vs. Part-time: Full-time	511	0.8949	0.903	0.8983	0.899	0.0074	0.6845	0.0357	4 [-14, 22]
Full-time vs. Part-time: Part-time	49	0.7513	0.522	0.7545	0.7065	-0.1813	0.0447*	0.177	-9 [-18, 0]
Gender: Female	331	0.8887	0.8784	0.888	0.8871	-0.0094	0.6921	0.0465	-3 [-19, 12]
Gender: Male	232	0.8753	0.8559	0.8772	0.8693	-0.0115	0.7043	0.0594	-3 [-16, 11]
Race: Asian	8	0.8715	0.8525	0.8755	0.8401	0.0163	0.9233	0.3571	0 [-3, 3]
Race: Black or African American	11	0.863	0.7	0.8902	0.9159	-0.1887	0.2368	0.3246	-2 [-6, 1]
Race: Pacific Islander	2	0.8735	1	0.8473	0.8373	0.1365	0.7165	3.6325	0 [-7, 8]
Race: Two or More	21	0.9028	0.9769	0.8923	0.8702	0.0962	0.2065	0.1518	2 [-1, 5]
Race: Unknown	8	0.882	0.8268	0.8759	0.8707	-0.05	0.772	0.3649	0 [-3, 3]
Race: White or Caucasian	508	0.8829	0.8696	0.883	0.8807	-0.011	0.5739	0.0384	-6 [-25, 14]
STEM Major: Not STEM	463	0.8829	0.874	0.8789	0.8761	-0.0061	0.7707	0.0411	-3 [-22, 16]
STEM Major: STEM	100	0.8841	0.8482	0.8972	0.8896	-0.0283	0.5101	0.0845	-3 [-11, 6]
Undergraduate Type: First Time in College	442	0.8891	0.8867	0.8895	0.8854	0.0016	0.9348	0.0392	1 [-17, 18]
Undergraduate Type: Readmit	53	0.8406	0.7498	0.8432	0.84	-0.0876	0.2509	0.1506	-5 [-13, 3]
Undergraduate Type: Transfer	63	0.8767	0.8439	0.869	0.8687	-0.0325	0.5971	0.1215	-2 [-10, 6]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F2.4

Lower Division Courses – 201720

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	552	0.8105	0.8084	0.8103	0.7764	0.0318	0.1663	0.045	18 [-7, 42]
Completed Terms: 0 Terms	42	0.6922	0.7146	0.6972	0.6784	0.0412	0.6364	0.1729	2 [-6, 9]
Completed Terms: 1-3 Terms	373	0.8134	0.8062	0.8119	0.7621	0.0426	0.1311	0.0553	16 [-5, 37]
Completed Terms: 4+ Terms	136	0.8382	0.8429	0.8436	0.8497	-0.0014	0.9738	0.086	0 [-12, 12]
Course Modality: All On-Ground	374	0.8052	0.8132	0.8052	0.7647	0.0484	0.0833	0.0548	18 [-2, 39]
Course Modality: All Online	11	0.7278	0.547	0.73	0.6609	-0.1117	0.5405	0.3743	-1 [-5, 3]
Course Modality: Mixed or Blended	165	0.8288	0.8142	0.8279	0.8113	0.0021	0.9598	0.0804	0 [-13, 14]
Ethnicity: Hispanic or Latino	12	0.7936	0.6342	0.8176	0.8232	-0.1649	0.3336	0.3477	-2 [-6, 2]
Ethnicity: Not Hispanic or Latino	539	0.8111	0.8109	0.8102	0.7755	0.0344	0.1371	0.0454	19 [-6, 43]
Full-time vs. Part-time: Full-time	463	0.8356	0.8359	0.838	0.8019	0.0364	0.1304	0.0471	17 [-5, 39]
Full-time vs. Part-time: Part-time	84	0.6845	0.6746	0.6945	0.6654	0.0192	0.7763	0.1332	2 [-10, 13]
Gender: Female	286	0.8306	0.8161	0.8153	0.7707	0.0302	0.3557	0.0641	9 [-10, 27]
Gender: Male	265	0.789	0.8002	0.8054	0.7825	0.0341	0.2918	0.0635	9 [-8, 26]
Race: American Indian/Alaskan Native	4	0.6976	0.3455	0.7997	0.842	-0.3944	0.0593	0.4142	-2 [-3, 0]
Race: Asian	8	0.7158	0.8991	0.8126	0.8446	0.1513	0.3088	0.3074	1 [-1, 4]
Race: Black or African American	9	0.7198	0.5046	0.7607	0.5614	-0.0159	0.9545	0.6641	0 [-6, 6]
Race: Pacific Islander	2	0.8141	0.7552	0.7891	0.8775	-0.1473	0.546	0.6915	0 [-2, 1]
Race: Two or More	13	0.7851	0.886	0.7612	0.6639	0.1983	0.0978	0.2371	3 [-1, 6]
Race: Unknown	12	0.7885	0.5435	0.7936	0.7436	-0.1951	0.2955	0.3847	-2 [-7, 2]
Race: White or Caucasian	499	0.8157	0.8183	0.8131	0.7801	0.0357	0.1358	0.0469	18 [-6, 41]
STEM Major: Not STEM	442	0.8089	0.795	0.7979	0.7654	0.0186	0.494	0.0532	8 [-15, 32]
STEM Major: STEM	110	0.8169	0.8646	0.8395	0.8023	0.0849	0.0493*	0.0846	9 [0, 19]
Undergraduate Type: First Time in College	407	0.8065	0.7923	0.8169	0.7776	0.0251	0.3489	0.0525	10 [-11, 32]
Undergraduate Type: Readmit	70	0.8245	0.8739	0.8096	0.8339	0.0251	0.6771	0.1191	2 [-7, 10]
Undergraduate Type: Transfer	67	0.8224	0.8405	0.7788	0.7218	0.0751	0.2484	0.128	5 [-4, 14]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F2.5

Lower Division Courses – 201740

Subgroup	Matched participants	Participant group Outcome predicted	Participant group Outcome actual	Control group Outcome predicted	Control group Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	512	0.8721	0.9005	0.8726	0.8735	0.0275	0.1537	0.0378	14 [-5, 33]
Completed Terms: 0 Terms	224	0.883	0.9054	0.8828	0.8965	0.0087	0.7516	0.0543	2 [-10, 14]
Completed Terms: 1-3 Terms	186	0.8559	0.8764	0.8743	0.8515	0.0433	0.2129	0.0682	8 [-5, 21]
Completed Terms: 4+ Terms	100	0.8774	0.9341	0.8464	0.8619	0.0412	0.3143	0.0805	4 [-4, 12]
Course Modality: All On-Ground	398	0.8751	0.9056	0.8754	0.8789	0.027	0.2068	0.042	11 [-6, 27]
Course Modality: All Online	1	0.744	1	0.7452	0.2986	0.7026	0.1525	2.1805	1 [-1, 3]
Course Modality: Mixed or Blended	111	0.8631	0.8803	0.8644	0.8586	0.023	0.6028	0.0868	3 [-7, 12]
Ethnicity: Hispanic or Latino	6	0.879	1	0.7858	0.8182	0.0887	0.5331	0.3255	1 [-1, 2]
Ethnicity: Not Hispanic or Latino	506	0.872	0.8993	0.874	0.8749	0.0264	0.1746	0.0381	13 [-6, 33]
Full-time vs. Part-time: Full-time	468	0.8879	0.912	0.8942	0.897	0.0213	0.2656	0.0376	10 [-8, 28]
Full-time vs. Part-time: Part-time	43	0.7012	0.7791	0.7308	0.723	0.0858	0.3138	0.1683	4 [-4, 11]
Gender: Female	283	0.8748	0.912	0.8754	0.8669	0.0457	0.076	0.0505	13 [-1, 27]
Gender: Male	226	0.8686	0.8872	0.8692	0.8813	0.0064	0.8251	0.0571	1 [-11, 14]
Race: Asian	8	0.8607	1	0.863	0.8025	0.1999	0.1542	0.293	2 [-1, 4]
Race: Black or African American	5	0.9382	0.9492	0.9036	0.9676	-0.0529	0.7263	0.4118	0 [-2, 2]
Race: Two or More	17	0.8585	0.9861	0.8859	0.9055	0.1079	0.1611	0.1551	2 [-1, 4]
Race: Unknown	28	0.8799	0.9136	0.873	0.867	0.0397	0.6654	0.1849	1 [-4, 6]
Race: White or Caucasian	445	0.8716	0.8951	0.8732	0.876	0.0207	0.32	0.0408	9 [-9, 27]
STEM Major: Not STEM	430	0.8705	0.9014	0.8636	0.8554	0.0391	0.0831	0.0442	17 [-2, 36]
STEM Major: STEM	82	0.88	0.8928	0.8997	0.9282	-0.0157	0.6826	0.0757	-1 [-7, 5]
Undergraduate Type: First Time in College	388	0.8777	0.9017	0.8826	0.8786	0.0281	0.2023	0.0432	11 [-6, 28]
Undergraduate Type: Readmit	51	0.8364	0.8873	0.8197	0.7943	0.0762	0.248	0.1302	4 [-3, 11]
Undergraduate Type: Transfer	69	0.8671	0.9026	0.8548	0.9047	-0.0144	0.7682	0.0965	-1 [-8, 6]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F2.6

Lower Division Courses – 201820

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	643	0.8167	0.8405	0.8158	0.792	0.0476	0.0213*	0.0405	31 [5, 57]
Completed Terms: 0 Terms	116	0.7558	0.794	0.7547	0.7909	0.002	0.9685	0.1002	0 [-11, 12]
Completed Terms: 1-3 Terms	400	0.8192	0.826	0.8241	0.7797	0.0511	0.0586	0.053	20 [-1, 42]
Completed Terms: 4+ Terms	125	0.866	0.9253	0.8434	0.8279	0.0749	0.0549	0.0765	9 [0, 19]
Course Modality: All On-Ground	446	0.8048	0.818	0.8046	0.7899	0.0279	0.2706	0.0497	12 [-10, 35]
Course Modality: All Online	7	0.6747	0.7689	0.671	0.6316	0.1336	0.5435	0.4716	1 [-2, 4]
Course Modality: Mixed or Blended	189	0.8492	0.8941	0.8469	0.7997	0.0921	0.0104*	0.0703	17 [4, 31]
Ethnicity: Hispanic or Latino	8	0.8148	0.8582	0.8167	0.7625	0.0976	0.6614	0.5243	1 [-3, 5]
Ethnicity: Not Hispanic or Latino	634	0.8167	0.8399	0.8159	0.7925	0.0466	0.0251*	0.0407	30 [4, 55]
Full-time vs. Part-time: Full-time	563	0.8333	0.8691	0.8344	0.807	0.0633	0.0032**	0.042	36 [12, 59]
Full-time vs. Part-time: Part-time	79	0.6979	0.6351	0.7092	0.7071	-0.0606	0.3702	0.1332	-5 [-15, 6]
Gender: Female	322	0.8318	0.8486	0.8266	0.7844	0.0591	0.0478*	0.0585	19 [0, 38]
Gender: Male	320	0.8014	0.832	0.8056	0.7994	0.0368	0.1991	0.0562	12 [-6, 30]
Race: American Indian/Alaskan Native	4	0.822	0.8187	0.7776	0.7317	0.0425	0.7666	0.3081	0 [-1, 1]
Race: Asian	3	0.8653	0.7378	0.8131	0.872	-0.1863	0.3359	0.4389	-1 [-2, 1]
Race: Black or African American	3	0.6692	0.7697	0.7954	0.6993	0.1966	0.4628	0.6537	1 [-1, 3]
Race: Two or More	14	0.797	0.8223	0.8046	0.8889	-0.059	0.6011	0.2296	-1 [-4, 2]
Race: Unknown	37	0.8203	0.8337	0.8102	0.8069	0.0167	0.8518	0.1786	1 [-6, 7]
Race: White or Caucasian	576	0.8176	0.8437	0.8179	0.79	0.054	0.0145*	0.0432	31 [6, 56]
STEM Major: Not STEM	529	0.8168	0.8377	0.8045	0.7723	0.0532	0.0297*	0.0479	28 [3, 53]
STEM Major: STEM	114	0.8165	0.8514	0.8427	0.8396	0.0381	0.3476	0.0797	4 [-5, 13]
Undergraduate Type: First Time in College	495	0.8153	0.851	0.8251	0.7952	0.0657	0.0052**	0.0461	33 [10, 55]
Undergraduate Type: Readmit	72	0.8163	0.8141	0.8106	0.772	0.0364	0.5726	0.1272	3 [-7, 12]
Undergraduate Type: Transfer	75	0.8264	0.7972	0.7796	0.7946	-0.0442	0.4436	0.1137	-3 [-12, 5]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F2.7

Lower Division Courses – 201840

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	615	0.8911	0.9093	0.8914	0.8922	0.0175	0.2913	0.0324	11 [-9, 31]
Completed Terms: 0 Terms	270	0.8842	0.9064	0.8825	0.8999	0.0049	0.8445	0.0487	1 [-12, 14]
Completed Terms: 1-3 Terms	223	0.8975	0.8984	0.9069	0.8968	0.0111	0.6821	0.0532	2 [-9, 14]
Completed Terms: 4+ Terms	119	0.8952	0.9357	0.881	0.8638	0.0577	0.1425	0.0772	7 [-2, 16]
Course Modality: All On-Ground	507	0.8907	0.9012	0.8909	0.8991	0.0024	0.8944	0.0358	1 [-17, 19]
Course Modality: Mixed or Blended	103	0.8931	0.9462	0.8938	0.8617	0.0852	0.0309*	0.0773	9 [1, 17]
Ethnicity: Hispanic or Latino	3	0.7368	0.6866	0.8069	0.8051	-0.0484	0.8633	0.8189	0 [-3, 2]
Ethnicity: Not Hispanic or Latino	611	0.8921	0.911	0.8919	0.8926	0.0181	0.2739	0.0325	11 [-9, 31]
Full-time vs. Part-time: Full-time	555	0.9042	0.9267	0.9079	0.9084	0.022	0.1749	0.0318	12 [-5, 30]
Full-time vs. Part-time: Part-time	58	0.7701	0.7504	0.7687	0.7724	-0.0234	0.7565	0.1493	-1 [-10, 7]
Gender: Female	348	0.8995	0.9055	0.8922	0.8973	0.001	0.9659	0.0438	0 [-15, 16]
Gender: Male	266	0.8802	0.9146	0.8905	0.8863	0.0387	0.1151	0.0482	10 [-3, 23]
Race: Asian	17	0.8857	0.8464	0.9104	0.9111	-0.04	0.7749	0.2995	-1 [-6, 4]
Race: Black or African American	7	0.9164	0.9457	0.8946	0.9833	-0.0594	0.5678	0.2238	0 [-2, 1]
Race: Two or More	19	0.8991	0.927	0.9014	0.9184	0.011	0.9078	0.1935	0 [-3, 4]
Race: Unknown	14	0.8357	0.7913	0.8898	0.9452	-0.0998	0.3677	0.2253	-1 [-5, 2]
Race: White or Caucasian	552	0.892	0.9134	0.8916	0.8925	0.0205	0.2357	0.0339	11 [-7, 30]
STEM Major: Not STEM	514	0.8873	0.897	0.8831	0.8845	0.0083	0.6733	0.0385	4 [-16, 24]
STEM Major: STEM	100	0.911	0.9722	0.9142	0.9138	0.0616	0.0191*	0.0514	6 [1, 11]
Undergraduate Type: First Time in College	499	0.8981	0.9177	0.8981	0.9041	0.0135	0.4419	0.0344	7 [-10, 24]
Undergraduate Type: Readmit	56	0.8483	0.906	0.8521	0.7962	0.1136	0.0876	0.1307	6 [-1, 14]
Undergraduate Type: Transfer	58	0.8749	0.8393	0.868	0.8762	-0.0439	0.4804	0.1228	-3 [-10, 5]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F3.1

Upper Division Courses – All Terms

		Participant group		Control group					
Subgroup	Matched participants	Outcome predicted	Outcome actual	Outcome predicted	Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	5015	0.916	0.9512	0.9174	0.952	0.0007	0.8696	0.0082	4 [-38, 45]
Completed Terms: 0 Terms	72	0.8297	0.8671	0.8238	0.8193	0.042	0.4676	0.1139	3 [-5, 11]
Completed Terms: 1-3 Terms	1069	0.8978	0.9398	0.8977	0.9353	0.0044	0.681	0.0212	5 [-18, 27]
Completed Terms: 4+ Terms	3882	0.9221	0.9548	0.9224	0.9563	-0.0012	0.7859	0.0089	-5 [-39, 30]
Course Modality: All On-Ground	2634	0.9225	0.952	0.9235	0.9525	0.0006	0.9221	0.0113	2 [-28, 31]
Course Modality: All Online	265	0.7921	0.8748	0.7929	0.8534	0.0223	0.4357	0.0561	6 [-9, 21]
Course Modality: Mixed or Blended	2124	0.9225	0.9578	0.9244	0.9613	-0.0016	0.7922	0.0118	-3 [-28, 22]
Ethnicity: Hispanic or Latino	196	0.9132	0.9589	0.9133	0.9521	0.0071	0.7365	0.0412	1 [-7, 9]
Ethnicity: Not Hispanic or Latino	4828	0.9157	0.95	0.9171	0.951	0.0005	0.9094	0.0085	2 [-39, 43]
Full-time vs. Part-time: Full-time	4404	0.9278	0.9613	0.9311	0.9659	-0.0014	0.7353	0.0078	-6 [-41, 28]
Full-time vs. Part-time: Part-time	616	0.8295	0.8729	0.8308	0.8597	0.0145	0.4314	0.036	9 [-13, 31]
Gender: Female	2757	0.9126	0.9552	0.9152	0.9507	0.0071	0.2095	0.011	20 [-11, 50]
Gender: Male	2267	0.9192	0.9444	0.919	0.9513	-0.007	0.2756	0.0126	-16 [-44, 13]
Race: American Indian/Alaskan Native	23	0.8993	0.921	0.9107	0.8867	0.0458	0.5528	0.154	1 [-2, 5]
Race: Asian	98	0.8904	0.9353	0.9082	0.9297	0.0234	0.5276	0.0729	2 [-5, 9]
Race: Black or African American	48	0.8878	0.9207	0.8597	0.9	-0.0074	0.9082	0.1271	0 [-6, 6]
Race: Pacific Islander	14	0.9314	0.9062	0.8932	0.9659	-0.0978	0.2513	0.1725	-1 [-4, 1]
Race: Two or More	105	0.9125	0.9307	0.9093	0.9568	-0.0293	0.3123	0.0571	-3 [-9, 3]
Race: Unknown	101	0.8863	0.9177	0.8777	0.9101	-0.001	0.979	0.0772	0 [-8, 8]
Race: White or Caucasian	4632	0.9171	0.9524	0.9187	0.9529	0.001	0.8134	0.0085	5 [-35, 44]
STEM Major: Not STEM	3430	0.9106	0.9525	0.9145	0.9494	0.007	0.1597	0.0097	24 [-9, 57]
STEM Major: STEM	1586	0.9276	0.9486	0.9261	0.9594	-0.0123	0.1175	0.0154	-20 [-44, 5]
Undergraduate Type: First Time in College	2140	0.9224	0.9602	0.9227	0.9538	0.0066	0.2767	0.012	14 [-12, 40]
Undergraduate Type: Readmit	1361	0.9165	0.9409	0.9199	0.9541	-0.0098	0.2424	0.0165	-13 [-36, 9]
Undergraduate Type: Transfer	1504	0.907	0.948	0.9084	0.9483	0.0011	0.8895	0.0156	2 [-22, 25]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F3.2

Upper Division Courses – 201620

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	640	0.9145	0.9458	0.917	0.9564	-0.008	0.5	0.0233	-5 [-20, 10]
Completed Terms: 1-3 Terms	141	0.9053	0.9414	0.8931	0.9353	-0.0061	0.8309	0.0558	-1 [-9, 7]
Completed Terms: 4+ Terms	498	0.9174	0.9472	0.9222	0.9606	-0.0085	0.5192	0.0259	-4 [-17, 9]
Course Modality: All On-Ground	390	0.9081	0.9404	0.9107	0.949	-0.006	0.7098	0.0316	-2 [-15, 10]
Course Modality: Mixed or Blended	250	0.9243	0.9541	0.9269	0.9682	-0.0115	0.5012	0.0336	-3 [-11, 6]
Ethnicity: Hispanic or Latino	34	0.904	0.9537	0.9052	0.9423	0.0126	0.8198	0.1104	0 [-3, 4]
Ethnicity: Not Hispanic or Latino	605	0.9151	0.945	0.9177	0.957	-0.0095	0.4354	0.0239	-6 [-20, 9]
Full-time vs. Part-time: Full-time	576	0.9234	0.9558	0.9269	0.9719	-0.0127	0.2534	0.0218	-7 [-20, 5]
Full-time vs. Part-time: Part-time	63	0.8328	0.8697	0.8426	0.841	0.0387	0.5125	0.1164	2 [-5, 10]
Gender: Female	349	0.9165	0.9683	0.9187	0.9593	0.0112	0.4259	0.0277	4 [-6, 14]
Gender: Male	291	0.912	0.9188	0.9154	0.9535	-0.0312	0.1161	0.039	-9 [-20, 2]
Race: American Indian/Alaskan Native	2	0.8801	0.7743	0.883	0.9038	-0.1267	0.6509	1.0385	0 [-2, 2]
Race: Asian	10	0.9259	1	0.9124	0.974	0.0125	0.7995	0.1018	0 [-1, 1]
Race: Black or African American	6	0.8792	0.887	0.9068	1	-0.0855	0.411	0.2437	-1 [-2, 1]
Race: Two or More	9	0.8757	1	0.8949	0.9634	0.0558	0.2175	0.0916	1 [0, 1]
Race: Unknown	16	0.9083	0.9269	0.8861	0.9291	-0.0244	0.7778	0.1752	0 [-3, 2]
Race: White or Caucasian	595	0.9154	0.9453	0.9189	0.9568	-0.0081	0.5143	0.0243	-5 [-19, 10]
STEM Major: Not STEM	432	0.9133	0.9583	0.9176	0.9578	0.0048	0.7072	0.025	2 [-9, 13]
STEM Major: STEM	207	0.9171	0.9209	0.9154	0.9519	-0.0327	0.2027	0.0504	-7 [-17, 4]
Undergraduate Type: First Time in College	289	0.9068	0.95	0.9101	0.9476	0.0057	0.7483	0.0351	2 [-8, 12]
Undergraduate Type: Readmit	175	0.9177	0.9283	0.9323	0.9705	-0.0276	0.2357	0.0458	-5 [-13, 3]
Undergraduate Type: Transfer	174	0.9232	0.9566	0.9107	0.9548	-0.0107	0.631	0.0437	-2 [-9, 6]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F3.3

Upper Division Courses – 201640

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	499	0.9223	0.9209	0.9235	0.8981	0.024	0.1832	0.0354	12 [-6, 30]
Completed Terms: 0 Terms	34	0.8849	0.953	0.8776	0.8383	0.1075	0.1344	0.142	4 [-1, 8]
Completed Terms: 1-3 Terms	111	0.9209	0.9406	0.9268	0.9022	0.0443	0.2785	0.0806	5 [-4, 14]
Completed Terms: 4+ Terms	355	0.9255	0.9109	0.9263	0.901	0.0107	0.6143	0.0416	4 [-11, 19]
Course Modality: All On-Ground	316	0.9249	0.9166	0.9265	0.8988	0.0194	0.3944	0.0447	6 [-8, 20]
Course Modality: Mixed or Blended	184	0.9162	0.9252	0.9168	0.8938	0.032	0.2828	0.0585	6 [-5, 17]
Ethnicity: Hispanic or Latino	33	0.925	0.9533	0.9207	0.9457	0.0033	0.9602	0.1342	0 [-4, 5]
Ethnicity: Not Hispanic or Latino	466	0.9214	0.9177	0.923	0.8949	0.0243	0.1954	0.0368	11 [-6, 28]
Full-time vs. Part-time: Full-time	461	0.9268	0.9335	0.9292	0.9062	0.0299	0.0959	0.0352	14 [-2, 30]
Full-time vs. Part-time: Part-time	38	0.8604	0.7617	0.8758	0.8352	-0.0581	0.4964	0.1695	-2 [-9, 4]
Gender: Female	271	0.9243	0.9489	0.9235	0.8995	0.0485	0.0323*	0.0444	13 [1, 25]
Gender: Male	229	0.9188	0.886	0.9223	0.8933	-0.0038	0.896	0.0567	-1 [-14, 12]
Race: American Indian/Alaskan Native	3	0.8513	1	0.9283	0.9741	0.103	0.3658	0.3521	0 [-1, 1]
Race: Asian	9	0.9267	0.903	0.9111	0.8671	0.0203	0.8921	0.3145	0 [-3, 3]
Race: Black or African American	8	0.9361	0.9176	0.9261	0.7894	0.1182	0.6496	0.7689	1 [-5, 7]
Race: Two or More	10	0.9451	1	0.9238	0.8911	0.0876	0.2734	0.166	1 [-1, 3]
Race: Unknown	9	0.9376	0.9219	0.8867	0.8041	0.0668	0.6897	0.3563	1 [-3, 4]
Race: White or Caucasian	460	0.9207	0.9187	0.9237	0.8999	0.0218	0.245	0.0368	10 [-7, 27]
STEM Major: Not STEM	356	0.9211	0.9523	0.9201	0.8947	0.0566	0.004**	0.0384	20 [6, 34]
STEM Major: STEM	143	0.9255	0.845	0.9319	0.9029	-0.0514	0.188	0.0767	-7 [-18, 4]
Undergraduate Type: First Time in College	230	0.9259	0.9314	0.9271	0.8951	0.0375	0.1454	0.0505	9 [-3, 20]
Undergraduate Type: Readmit	115	0.923	0.8727	0.9206	0.9016	-0.0314	0.4344	0.0789	-4 [-13, 5]
Undergraduate Type: Transfer	151	0.9183	0.9389	0.9215	0.9022	0.0399	0.2234	0.0644	6 [-4, 16]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F3.4

Upper Division Courses – 201720

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	905	0.9125	0.9535	0.9142	0.9473	0.0079	0.4239	0.0194	7 [-10, 25]
Completed Terms: 0 Terms	8	0.5595	0.678	0.5634	0.4724	0.2095	0.3887	0.5073	2 [-2, 6]
Completed Terms: 1-3 Terms	215	0.89	0.9156	0.8919	0.9242	-0.0068	0.7938	0.0509	-1 [-12, 9]
Completed Terms: 4+ Terms	684	0.9224	0.9675	0.9218	0.9552	0.0116	0.2543	0.02	8 [-6, 22]
Course Modality: All On-Ground	524	0.9103	0.9587	0.9115	0.9461	0.0138	0.2753	0.0249	7 [-6, 20]
Course Modality: All Online	28	0.6871	0.8116	0.6876	0.73	0.0822	0.4393	0.2115	2 [-4, 8]
Course Modality: Mixed or Blended	355	0.9309	0.9538	0.9333	0.9611	-0.0048	0.7497	0.0293	-2 [-12, 9]
Ethnicity: Hispanic or Latino	33	0.9071	0.9795	0.9066	0.9874	-0.0083	0.8006	0.0659	0 [-2, 2]
Ethnicity: Not Hispanic or Latino	875	0.9113	0.9511	0.9131	0.9429	0.01	0.3335	0.0202	9 [-9, 26]
Full-time vs. Part-time: Full-time	776	0.9259	0.9587	0.931	0.9646	-0.0008	0.931	0.0188	-1 [-15, 14]
Full-time vs. Part-time: Part-time	130	0.8284	0.9108	0.8148	0.838	0.0592	0.1162	0.074	8 [-2, 17]
Gender: Female	528	0.9095	0.9477	0.9144	0.9358	0.0168	0.2423	0.0281	9 [-6, 24]
Gender: Male	380	0.9135	0.9582	0.9114	0.9542	0.0019	0.8881	0.027	1 [-10, 11]
Race: American Indian/Alaskan Native	6	0.9157	0.9208	0.9332	0.9359	0.0024	0.9919	0.9302	0 [-6, 6]
Race: Asian	27	0.8774	0.9346	0.9023	0.8266	0.1329	0.3109	0.2753	4 [-4, 11]
Race: Black or African American	4	0.8027	0.6496	0.7319	0.856	-0.2771	0.2354	0.5178	-1 [-3, 1]
Race: Two or More	17	0.8906	0.9584	0.8998	0.9909	-0.0233	0.6844	0.1173	0 [-2, 2]
Race: Unknown	13	0.8581	0.9506	0.8585	0.938	0.0131	0.8609	0.1515	0 [-2, 2]
Race: White or Caucasian	839	0.914	0.9538	0.9154	0.9456	0.0096	0.3494	0.0201	8 [-9, 25]
STEM Major: Not STEM	620	0.909	0.9449	0.9117	0.9392	0.0083	0.5103	0.0247	5 [-10, 20]
STEM Major: STEM	284	0.92	0.9726	0.9207	0.9686	0.0046	0.752	0.0286	1 [-7, 9]
Undergraduate Type: First Time in College	383	0.9186	0.9582	0.9157	0.9526	0.0028	0.8503	0.0289	1 [-10, 12]
Undergraduate Type: Readmit	232	0.9246	0.9805	0.9249	0.9451	0.0357	0.0412*	0.0343	8 [0, 16]
Undergraduate Type: Transfer	289	0.8947	0.9262	0.9037	0.9425	-0.0073	0.7057	0.0381	-2 [-13, 9]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F3.5

Upper Division Courses – 201740

		Participant group		Control group					
Subgroup	Matched participants	Outcome predicted	Outcome actual	Outcome predicted	Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	943	0.912	0.9667	0.9129	0.9602	0.0074	0.3857	0.0168	7 [-9, 23]
Completed Terms: 0 Terms	14	0.8745	0.9969	0.8735	0.9512	0.0447	0.4472	0.1213	1 [-1, 2]
Completed Terms: 1-3 Terms	170	0.8971	0.9718	0.9001	0.9409	0.0339	0.1539	0.0466	6 [-2, 14]
Completed Terms: 4+ Terms	758	0.916	0.965	0.9158	0.9634	0.0014	0.8825	0.0183	1 [-13, 15]
Course Modality: All On-Ground	437	0.9358	0.9719	0.9367	0.9719	0.0009	0.9302	0.0211	0 [-9, 10]
Course Modality: All Online	100	0.8074	0.9238	0.8085	0.873	0.0519	0.2183	0.0829	5 [-3, 13]
Course Modality: Mixed or Blended	405	0.9122	0.9715	0.9131	0.9683	0.004	0.7463	0.0242	2 [-8, 11]
Ethnicity: Hispanic or Latino	29	0.9169	1	0.9199	0.9852	0.0178	0.4496	0.0467	1 [-1, 2]
Ethnicity: Not Hispanic or Latino	914	0.9118	0.9657	0.9126	0.9589	0.0075	0.3957	0.0174	7 [-9, 23]
Full-time vs. Part-time: Full-time	811	0.9267	0.9783	0.929	0.9769	0.0037	0.6224	0.0148	3 [-9, 15]
Full-time vs. Part-time: Part-time	132	0.8214	0.8954	0.82	0.862	0.032	0.415	0.0771	4 [-6, 14]
Gender: Female	487	0.902	0.9737	0.9089	0.9665	0.014	0.1995	0.0214	7 [-4, 17]
Gender: Male	455	0.9226	0.9594	0.9182	0.9511	0.0039	0.7773	0.0268	2 [-10, 14]
Race: American Indian/Alaskan Native	3	0.8526	1	0.9263	0.9462	0.1274	0.1393	0.1765	0 [0, 1]
Race: Asian	12	0.8711	1	0.9163	0.9544	0.0908	0.1156	0.1149	1 [0, 2]
Race: Black or African American	10	0.9059	1	0.857	0.7951	0.1559	0.3163	0.3471	2 [-2, 5]
Race: Pacific Islander	5	0.9163	0.678	0.8565	0.8229	-0.2047	0.4892	1.0549	-1 [-6, 4]
Race: Two or More	22	0.9343	0.9296	0.9031	0.9526	-0.0542	0.4003	0.1287	-1 [-4, 2]
Race: Unknown	18	0.8889	1	0.8687	0.9443	0.0355	0.5254	0.1147	1 [-1, 3]
Race: White or Caucasian	872	0.9126	0.9676	0.9145	0.9627	0.0069	0.4322	0.0172	6 [-9, 21]
STEM Major: Not STEM	617	0.9003	0.9648	0.9092	0.9553	0.0185	0.0829	0.0209	11 [-1, 24]
STEM Major: STEM	325	0.9343	0.9705	0.9265	0.9785	-0.0158	0.244	0.0266	-5 [-14, 4]
Undergraduate Type: First Time in College	359	0.9275	0.9716	0.9272	0.962	0.0092	0.4874	0.026	3 [-6, 13]
Undergraduate Type: Readmit	284	0.9048	0.9532	0.905	0.9585	-0.005	0.7677	0.0336	-1 [-11, 8]
Undergraduate Type: Transfer	294	0.9013	0.9729	0.903	0.959	0.0156	0.2883	0.0289	5 [-4, 13]
Undergraduate Type: Unknown Undergraduate Type	2	0.726	1	0.7578	1	0.0318	0.832	0.6447	0 [-1, 1]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F3.6

Upper Division Courses – 201820

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	1,105	0.9137	0.9394	0.9159	0.955	-0.0134	0.1463	0.018	-15 [-35, 5]
Completed Terms: 0 Terms	3	0.6359	0.7019	0.6284	0.7528	-0.0584	0.8768	0.984	0 [-3, 3]
Completed Terms: 1-3 Terms	272	0.8766	0.9213	0.8841	0.9264	0.0024	0.9187	0.046	1 [-12, 13]
Completed Terms: 4+ Terms	831	0.9265	0.9455	0.9238	0.9615	-0.0186	0.0596	0.0194	-15 [-32, 1]
Course Modality: All On-Ground	489	0.917	0.9494	0.918	0.9617	-0.0114	0.3765	0.0252	-6 [-18, 7]
Course Modality: All Online	110	0.7914	0.8256	0.7926	0.8635	-0.0367	0.4288	0.0912	-4 [-14, 6]
Course Modality: Mixed or Blended	507	0.9364	0.9532	0.94	0.9666	-0.0097	0.4275	0.024	-5 [-17, 7]
Ethnicity: Hispanic or Latino	35	0.904	0.9064	0.909	0.8653	0.046	0.531	0.146	2 [-4, 7]
Ethnicity: Not Hispanic or Latino	1,071	0.9137	0.9397	0.9157	0.9566	-0.0149	0.1067	0.0181	-16 [-35, 3]
Full-time vs. Part-time: Full-time	951	0.9306	0.9542	0.9342	0.9696	-0.0118	0.1792	0.0172	-11 [-28, 5]
Full-time vs. Part-time: Part-time	155	0.8081	0.8447	0.8222	0.8764	-0.0176	0.6236	0.0706	-3 [-14, 8]
Gender: Female	660	0.9103	0.9347	0.9122	0.9518	-0.0153	0.2166	0.0244	-10 [-26, 6]
Gender: Male	445	0.918	0.945	0.9196	0.9568	-0.0101	0.4635	0.0271	-4 [-17, 8]
Race: American Indian/Alaskan Native	6	0.9017	0.8463	0.8658	0.6381	0.1724	0.4015	0.4321	1 [-2, 4]
Race: Asian	22	0.8743	0.9258	0.8828	0.9676	-0.0332	0.6204	0.1342	-1 [-4, 2]
Race: Black or African American	11	0.8479	0.886	0.8431	0.9782	-0.097	0.3961	0.2356	-1 [-4, 2]
Race: Pacific Islander	2	0.9376	1	0.8945	1	-0.0431	0.2388	0.0965	0 [0, 0]
Race: Two or More	26	0.9057	0.83	0.9131	0.9435	-0.1062	0.1791	0.1567	-3 [-7, 1]
Race: Unknown	25	0.8442	0.8637	0.8669	0.8796	0.0068	0.9436	0.1925	0 [-5, 5]
Race: White or Caucasian	1,011	0.9169	0.944	0.9184	0.9579	-0.0123	0.1849	0.0181	-12 [-31, 6]
STEM Major: Not STEM	812	0.9086	0.9346	0.9122	0.9559	-0.0177	0.0997	0.021	-14 [-31, 3]
STEM Major: STEM	292	0.9279	0.9528	0.927	0.9519	0.0001	0.9948	0.0351	0 [-10, 10]
Undergraduate Type: First Time in College	452	0.9225	0.9577	0.9218	0.9648	-0.0079	0.5294	0.0245	-4 [-15, 8]
Undergraduate Type: Readmit	298	0.9209	0.9147	0.9234	0.9636	-0.0464	0.0114*	0.0359	-14 [-25, -3]
Undergraduate Type: Transfer	353	0.8977	0.9387	0.9038	0.9381	0.0068	0.704	0.0353	2 [-10, 15]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

Table F3.7

Upper Division Courses – 201840

Subgroup	Matched participants	Participant group: Outcome predicted	Participant group: Outcome actual	Control group: Outcome predicted	Control group: Outcome actual	Outcome diff.	*p* value	CI	Persisted
Academic Level: Undergraduate	922	0.9237	0.9675	0.9238	0.9707	-0.003	0.702	0.0156	-3 [-17, 12]
Completed Terms: 0 Terms	10	0.8756	0.6747	0.873	0.9094	-0.2373	0.1763	0.3563	-2 [-6, 1]
Completed Terms: 1-3 Terms	158	0.9226	0.9698	0.9128	0.9781	-0.0182	0.3419	0.0375	-3 [-9, 3]
Completed Terms: 4+ Terms	754	0.9245	0.9686	0.926	0.9693	0.0008	0.9269	0.017	1 [-12, 13]
Course Modality: All On-Ground	477	0.9394	0.9617	0.9389	0.97	-0.0088	0.4446	0.0225	-4 [-15, 7]
Course Modality: All Online	26	0.8534	0.9665	0.8533	0.8874	0.079	0.2749	0.1441	2 [-2, 6]
Course Modality: Mixed or Blended	421	0.9101	0.9695	0.9108	0.9745	-0.0042	0.7068	0.0219	-2 [-11, 7]
Ethnicity: Hispanic or Latino	29	0.9272	0.9625	0.9204	0.9742	-0.0185	0.702	0.0969	-1 [-3, 2]
Ethnicity: Not Hispanic or Latino	894	0.9235	0.9654	0.9237	0.9698	-0.0042	0.6074	0.0162	-4 [-18, 11]
Full-time vs. Part-time: Full-time	827	0.931	0.9743	0.9335	0.98	-0.0032	0.6574	0.0144	-3 [-15, 9]
Full-time vs. Part-time: Part-time	97	0.8604	0.8857	0.8486	0.8916	-0.0176	0.6913	0.0875	-2 [-10, 7]
Gender: Female	459	0.9209	0.9683	0.92	0.9676	-0.0002	0.9864	0.0224	0 [-10, 10]
Gender: Male	465	0.9264	0.9625	0.9278	0.9721	-0.0082	0.4777	0.0227	-4 [-14, 7]
Race: Asian	16	0.8932	0.8653	0.9326	0.9522	-0.0475	0.6358	0.204	-1 [-4, 3]
Race: Black or African American	7	0.9394	1	0.9271	0.9741	0.0136	0.8686	0.2312	0 [-2, 2]
Race: Pacific Islander	5	0.9263	1	0.9326	1	0.0063	0.8746	0.1399	0 [-1, 1]
Race: Two or More	19	0.9139	0.9787	0.9303	0.9815	0.0136	0.7565	0.0883	0 [-1, 2]
Race: Unknown	19	0.9128	0.8753	0.9073	0.9129	-0.0431	0.6754	0.2093	-1 [-5, 3]
Race: White or Caucasian	853	0.9244	0.9682	0.9236	0.9702	-0.003	0.7185	0.0162	-3 [-16, 11]
STEM Major: Not STEM	590	0.9175	0.9683	0.9202	0.9671	0.004	0.6872	0.0193	2 [-9, 14]
STEM Major: STEM	332	0.9347	0.9659	0.9354	0.9827	-0.0162	0.2093	0.0253	-5 [-14, 3]
Undergraduate Type: First Time in College	425	0.9305	0.9767	0.9314	0.9712	0.0065	0.5506	0.0214	3 [-6, 12]
Undergraduate Type: Readmit	255	0.913	0.9617	0.9176	0.9651	0.0012	0.9428	0.033	0 [-8, 9]
Undergraduate Type: Transfer	241	0.9229	0.9577	0.9174	0.9744	-0.0222	0.1591	0.031	-5 [-13, 2]

* $p < .05$, ** $p < .01$, *** $p < .001$, 95% CI

CURRICULUM VITAE

JOHN LOUVIERE

EDUCATION

Ph.D., School of Teacher Education and Leadership (TEAL) — 2020
Curriculum & Instruction
Utah State University, Logan, Utah, USA

- Concentration: Instructional Leadership
- Emphasized coursework in educational leadership, analytics
- Dissertation: Louviere, J. (2019). *Persistence Impacts on Student Subgroups that Participate in the High Impact Practice of Service Learning.*

M.S. School of Instructional Technology and Learning Sciences (ITLS) — 2000
Instructional Technology
Utah State University, Logan, Utah, USA

- Emphasis: Online Learning and Adult Education

B.S. School of Industrial Education — 1998
Industrial Teacher Education

- Utah State License in Secondary Education
- Endorsement: Vocational Education

Minor School of Languages — 1998
Czech
Utah State University, Logan, Utah, USA

CURRENT ROLE

Executive Director & Assistant Vice President — Oct. 2017 - present
Academic and Instructional Services
Utah State University, Logan, Utah, USA

Executive Director & Assistant Dean — Dec. 2015 – Oct. 2017
Academic and Instructional Services
Utah State University, Logan, Utah, USA

Chief Learning Officer — Jan. 2016 – Nov. 2017
Unizin
Austin, Texas, USA

Director — Sept. 2012 – Dec. 2015
Center for Innovative Design & Instruction
Utah State University, Logan, Utah, USA

Senior Instructional Designer and LMS Administrator — Mar. 2011 – Sept. 2012
Faculty Assistance Center for Teaching
Utah State University, Logan, Utah, USA

Instructional Designer — Jul. 2007 – Feb. 2011
Faculty Assistance Center for Teaching
Utah State University, Logan, Utah, USA

Director — Sept. 2004 – Jul. 2007
Outdoor Recreation Center
Utah State University, Logan, Utah, USA

Programs Officer/Manager — Dec. 2000 – Aug. 2004
Colorado Institute of Technology
Broomfield, Colorado, USA

Technology and Algebra Teacher — Aug. 1997 – Jul. 1998
Box Elder Middle School
Brigham City, Utah, USA

PUBLICATIONS

Eastmond, J. N., Louviere, J., & Quinn, K. (2008). Redesigning a Research Methods Course for Teachers. TechTrends, 52(6), 23.

MANAGED PUBLICATIONS

Colorado's Action Plan to Grow Colorado's Bioscience Cluster. (2003, May). Battelle Memorial Institute.

Global Telecommunications Planning Study. (2002, September). University of Colorado at Boulder.

Labor Market Information on a Colorado Specific High-Tech Job Vacancy Report. (2001, November). Colorado Department of Labor and Employment.

PROFESSIONAL PRESENTATIONS

USU Architecture for Engagement. (2019, October). Association for Public Land Grant University western cluster conference.

A Tale of Two Strategies. (2019, March). Co-presenters, Matt Devlin, Rene Eborn, Dr. Robert Wagner. University Professional and Continuing Education Association.

USU Quality Workforce Initiative for Student Success. (2018, September). Co-presenter, Dr. Robert Wagner. Utah OPS: Building on Success conference.

All Your Data in One Place to Build and Explore. (2017, April). Co-presenter, Dr. Mitchell Colver. Civitas Learning Summit.

Using analytic insights to accomplish institutional goals for advising, retention, teaching & learning, and university business. (2016, July). Utah System of Higher Education, Chief Academic Officers retreat.

Tool Development for the Canvas LMS. (2016, July). WESTNET, CIOs.

Institutional Use of Analytics. (2016, June). Instructurecon conference.

Newton's Third Law and Organizational Change: To Act or Be Acted Upon. (2014, November). Western Interstate Commission for Higher Education conference.

Canvas APIs for the Rest of Us. (2014, June). Instructurecon, pre-conference workshop.

Ensuring Teaching Excellence: An Ecosystem of Instructional Support. (2013, November). Western Interstate Commission for Higher Education conference.

Canvas APIs for the Rest of Us. (2013, June). Instructurecon, pre-conference workshop.

Leveraging Canvas APIs to Populate a Data Warehouse Used to Research Instructional Design and Teaching Practices. (2013, June). Instructurecon conference.

Providing Substantial Evidence that a Degree Aligns with Industry Needs. (2013, March). Scholarship of Teaching and Engagement conference.

A Sustainable Support Structure: ADA Compliance and Online Access to Course Materials. (2012, October). University Professional and Continuing Education Association – UPCEA conference.

Accreditation, Oh That Silly Thing: Using Outcomes to Satisfy Accreditation Needs. (2012, June). Instructurecon conference.

Canvas for Blackboard Vista Users. (2011, June). Instructurecon conference.

Full Immersion American Sign Language Training in an Online Environment. (2010, November). South West Technology Showcase.

Jazz Up Your Blackboard Course with Javascript, jQuery, and CSS. (2010, November). South West Technology Showcase.

Using Blackboard with SCORM. (2008, July). Blackboard World 08 conference.

Using CSS in Blackboard. (2008, March). South West Blackboard Vista User's Conference.

How to Develop Courses Using SCORM Standards. (2008, March). South West Blackboard Vista User's Conference.

Proposal Writing for Institutions of Higher Education. (2003, August). Colorado Institute of Technology workshop.

Genetics in Practice: A Web-based Simulation Template. (2000, October). Association for Educational Communications Technology (AECT) conference.

Using Path Simulation in WebCT and Flash to Teach. (2000, October). Co-presentation with J.N. Eastmond. Association for Educational Communications Technology (AECT) conference.

Alpine Trainer: National Ski Patrol Certified Online Courses to Facilitate Winter Backcountry Use. (2000, October). International Snow Safety Conference.

Using Path Simulations to Teach Research Design Using WebCT and Flash. (2000, August). Utah State University Instructional Technology Institute.

Integrating Cold Fusion, Flash and WebCT for Instructional Development and Simulations. (2000, April). Utah State University Technology Expo.