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# Can We Improve Student Achievement through Multiple Interventions? A Test of Theory

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CAN A MULTIPLE-INTERVENTIONS APPROACH IMPROVE COLLEGE
STUDENT PERSISTENCE, GPA, AND CREDITS EARNED?

by

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## ABSTRACT

The research conducted tested a theory based on work by Tinto (1999), Astin (1984), and the Center for Community College Student Engagement (CCCSE, 2012) that multiple interventions are needed to significantly improve graduation rates at community colleges. The literature says little about this approach for community college students; therefore, this dissertation contributes to the knowledge base for educational programs.

A first-year program at a large, diverse community college using multiple interventions assisted in determining the validity of the theory. The interventions built into the first-year program included learning communities, a student success course (SSC), proactive advising, and experiential learning. The CCCSE and others identified these components as high-impact practices for improving student achievement. A common theme and faculty tied interventions together across the first year of the program. The small sample ($n = 21$) and the fact this was the pilot year represent the most critical limitations in ascertaining the efficacy of the theory.

The program's outcomes were evaluated using propensity score matching (PSM). Updates in statistical software continue to make the method easier to implement and evaluate. Consequently, this method is increasing in popularity in education to determine causality where random assignment is not feasible. Hence, the dissertation spends some time describing the method, so others can benefit from the method in their research. The author compared the program group to matched students from the same campus in the fall and spring terms. Characteristics of the match were chosen based on

a careful search of the literature and historical data of the institution to ensure that students in the match group would be comparable. Differences in persistence, grade point average (GPA), and credits earned served to determine the effectiveness of the theory in this pilot.

The program did not show a statistically significant increase ($p > .1$) in persistence, GPA, or credits earned over the matched group. Yet, a small effect was measured for GPA ($d = 0.51$, fall and $d = 0.12$, spring), credits earned ($d = 0.17$, fall and $d = 0.13$, spring), and persistence ($OR = 1.28$, fall and $OR = 1.25$, spring). The positive finding encourages more research into the theory of multiple interventions for community college students.

In conclusion, future research should include following up with the participants in year two to determine how long the intervention effect persists. Also, increasing the sample size by including other first-year programs run by the institution improves the ability to detect differences and improve confidence. Finally, multiple interventions need to be tried on many different types of students to determine who benefits most.

This dissertation is dedicated to my wife, Shanna, and my children, Deven, Hailey, Ashlyn, Alexa, Juliet, and Tristan. Without your support and understanding, this project would not have been possible. Thank you for walking with me toward a lifelong dream.

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**CHAPTER ONE: INTRODUCTION**

<u>Graduation Rates: A National Issue</u>

Falling college graduation rates pose a national problem (CCCSE, 2012; Price & Tovar, 2014; Shapiro, Dundar, Yuan, Harrell, & Wakhungu, 2014). Only 56% of first-time college students entering in the fall of 2007 graduated after six years, and this phenomenon increased further in 2008 with rates dropping to 55.0% (Shapiro et al., 2014). These data represent 96% of all students who would have been enrolled in college, according to the National Student Clearinghouse, which ensures unduplicated counting across institutions. Even worse, less than 40% of two-year college students from the same time period completed their degrees or transferred to a four-year institution (Shapiro et al., 2014). Also, Juszkiewicz (2014) estimates community college students complete degrees at either 21% or 40% depending on the data source referenced. Either way, these percentages represent the alarming fact that many struggle to graduate.

Furthermore, not graduating from college has implications that extend into every aspect of a student's life. Nasiripour (2016) reported that for 2016 delinquencies on student loans are around 20% and on-time payments are only 58%. The National Association of Realtors expressed concern in June 2016 that student-loan debt is affecting first-time home buying. Consequently, student completion rates affect many areas of a student's financial life. This problem is significant enough for many national organizations and the White House to not simply call for more students to enroll but persist to degree completion (Price & Tovar, 2014).

Price and Tovar (2014) also report that community colleges allow access for underserved populations: minorities, low income, and first generation in college. Students who desire to rise above their circumstances with a college education and professional career. Students who wish to buy a home, get married, and pay off their debts. So, while community colleges can help change students' lives, the facts demonstrate that colleges need to improve in meeting the goal of not leaving students behind.

Even when looking at high-performing states, such as Florida, from the same region as the study was conducted, the completion rate for two-year college students entering in 2008 is still just 52% (Shapiro, Dundar, Wakhungu, Yuan, & Harrell, 2015). While this indicates that community colleges in Florida exceed the national average, institutions must continue to innovate when only one of every two students completes a degree. As previously noted, students who do not complete degrees may end up with student-loan debt, less earning potential, and delayed home-buying opportunities (Nasiripour, 2016; NAR, 2016).

<u>Graduation Rates: An Institutional Issue</u>

The community college studied (hereafter referred to as *the institution*) is a recognized leader in community colleges. Located in the Southeastern United States, the college serves more than 60,000 students a year at its multiple campuses. The student body is extremely diverse in terms of ethnicity, age, and socio-economic status. The institution is located near the local university, convincing many students to transfer after completion of a two-year degree.

Nevertheless, data reported by the institution indicate that only 44% of students graduate within 150% of the time required to finish their programs. Another 13% transfer to another institution without completing their programs, potentially bringing total persistence to around 57%. Hence, the institution is exceeding the national average of 40% and could actually surpass the Florida average of 52% (Shapiro et al., 2014; Shapiro et al., 2015). Even so, the fact remains that four students out of 10 are leaving the institution without achieving a degree or transfer success. Therefore, work still remains to be done in assisting every student toward his or her higher education goals.

<u>Can Multiple Interventions Work? A Test of Theory</u>

The Center for Community College Student Engagement (CCCSE) is a national organization seeking to improve student achievement at all two-year colleges. In *A Matter of Degrees: Promising Practices for Community College Student Success (A First Look),* the CCCSE synthesized results from national surveys and initiatives to determine what really affects student achievement. The Center's report describes (13) promising practices in community colleges for helping institutions promote improvements in student learning, persistence, and degree completion. Taken with Astin's (1984) theory of student involvement, lead to a working hypothesis that multiple interventions are needed to truly change graduation rates. The interventions and theoretical support are explored in detail in the Literature Review.

Thus, to test whether multiple interventions can truly improve student outcomes, this dissertation used quantitative methods to measure the impact of a pilot program (hereafter referred to as *the first-year program*). The first-year program integrates four

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interventions that previously were researched separately and recommended by the CCCSE (2012). The program description section provides a detailed explanation of the components and timeline. The student outcomes of interest include persistence at the college after two semesters, GPA after fall and spring terms, and credits earned after the fall and spring terms (Robbins et al., 2004). Therefore, the research questions focused on these benchmarks because if students are continually enrolling and earning credits while maintaining an adequate GPA, students will eventually attain their higher-education goals.

To assess the first-year program, the author used propensity score matching (PSM) to create a quasi-experimental design. The benefit from this method lies in the ability to make causal conclusions in an observational study, where traditionally making such inferences required a randomized control trial (Kim & Steiner, 2016). The field of education increasingly uses PSM due to its ability to reduce bias and determine causal effects (Frye, 2014; Ripley, 2015) and growing access to this method due to updates in common software packages. Therefore, the dissertation devotes sections to helping other practitioners understand and implement this tool. After matching, suitable statistical tests determined if the program reached its goals of improving student persistence and general achievement. As the program is being piloted, the outcomes could have been positive or negative. Therefore, the statistical tests remain non-directional and the research questions are consistent with this decision.

## Research Questions

1. To what extent does the persistence rate of students who participated in the program differ from a matched comparison group of students who do not participate?

2. To what extent does the GPA of students who participated in the program differ from a matched comparison group of students who do not participate?

3. To what extent do the credits earned of students who participated in the program differ from a matched comparison group of students who do not participate?

## Exploratory Question

4. What was the measured impact of the program on student achievement, specifically credits earned?

## Purpose and Scope

The purpose of this dissertation was to verify the theory of multiple-interventions using a quasi-experimental study design to determine if multiple interventions improve educational outcomes for program participants. This research study was limited to the quantitative data collected by the institution and does not represent a full program evaluation. The first-year pilot program developed by the institution, which uses multiple interventions, provided the evidence for the test of theory.

This study addressed the need to evaluate the new program to determine its effectiveness in increasing student success. The additional resources spent on these

students could have been allocated elsewhere in the institution. Consequently, it is prudent to determine if the program worked as implemented or needs changes to meet its stated goals. Hence, this study focused primarily on the theory that multiple interventions work in improving measurable student outcomes.

A full program evaluation was conducted by others in the institution to ensure the program was worthwhile. Therefore, no surveys, interviews, or focus groups conducted by the institution inform the study. Furthermore, the degree to which the interventions were implemented was not examined. The strength of the study however, rested on a design and methods that can be used anywhere. Because only demographic and achievement data normally collected from all students was needed, the causal impact of programs following the methods outlined can be determined by colleges and universities using existing data.

The analysis will assist in the development of the first-year program, identifying areas where goals are being met or improvement is needed. The results of the study will contribute to the institution's full program evaluation, which should lead to future improvements. The author hopes other institutions will be aided in the creation of programs aiming to increase student success.

<u>A First-Year Program</u>

Rationale for the Program

The CCCSE (2012) recommends multiple approaches at scale to improve student success. The institution took the high-impact practices recommended and transformed a previously successful program into the first-year program studied. To

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bring the program to scale, the analysis provided during this pilot year will be used to plan future cohorts. The limit on the number of cohorts run on the institution's five campuses will depend upon the number of unique degree pathways that can be developed (Business, STEM, Social and Behavioral Sciences, etc.) and the number of students needing those pathways. Applying all the lessons learned during the pilot should result in more effective programing in the future. Then, successful first-year programs could see widespread use that would impact a large number of students.

The desired result of implementing multiple improved first-year programs will be a closing of the gap between the institution's graduation rates and the high-performing Florida average. Using published numbers from the research, that gap stands at 9% (53% - 44%). The ability to scale the first-year program model and take lessons learned from it into other programs should close that gap. However, implementing and improving programs at scale take time. The evaluation of the first-year program took the 2016-2017 academic year. Currently, there is a plan to implement more cohorts for the 2017-2018 academic year (bringing the total to four cohorts on two campuses). Therefore, the timeline to bring the program to scale and implement lessons in other programs will take at least two years. Beyond that, program changes and implementation at other campuses will take more time.

## Program Description

When students engage with their courses and college activities, higher levels of success follow (Astin, 1984; CCCSE, 2012). Therefore, the first-year program increased engagement with the curriculum as a mechanism to raise levels of persistence, credits

earned, and GPA. The components of the model — learning communities, proactive

advising, student success course (SSC), and experiential learning — were all

components identified by the CCCSE (2012) and the institution (personal

communication, August 2016) as high-impact practices that increase student

achievement, as illustrated in *Figure 1*.

| Actions | Goals | Outcomes |
|---|---|---|
| • Faculty create a learning community through shared theme/classes<br>• Experiences outside the classroom build application and connection<br>• Advisor uses proactive advising through communication and appointments<br>• Students learn academic skills and become aware of resources through the student success course | • Students feel connected to the institution and integrate into the culture<br>• Students use the tools needed to be successful<br>• Students learn content and become academically ready | • Students persist at the institution through their first year<br>• Students increase the number of credits earned due to interventions<br>• Students increase GPA due to the interventions |

*Figure 1*. The Interventions Model.

Students accepted into the program experienced the multiple intervention

approaches. They attended all classes and activities as a cohort. The class scheduling

and activities worked due to the restriction that all 26 students be declared business

majors who had not taken any courses scheduled in the program. On the administrative

side, one advisor and six faculty members represented the program to the students.

While the business advisor assigned to the program included program students as part

of her regular duties, the faculty all volunteered and received a stipend for the extra

work the program requires. Moreover, the institution added administrative support for the entire program to ensure success and implementation.

The institution holds orientations specifically for business students. During those orientations, the business advisor assigned to the cohort explained the program and invited students interested to see her during the registration time for more information. Then, the advisor checked to make sure the students understood the program requirements and its benefits before directing them to apply online. Afterwards, students applied on a website that is one page and asks for basic information. Finally, the administration checked all the applications to make sure the students were declared business majors and had not taken any courses in the program. If these two criteria were met, students were accepted into the program in the order in which they applied. No other restrictions were placed on placement in the program. After the 26 spots filled, a wait list was created in case anyone dropped before the start of classes. This open policy led to a diverse group of students with different high school GPAs, parental levels of education, and demographic backgrounds being accepted. Thus, the cohort possessed traits that research shows negatively impact student outcomes (Astin, 1984, 1997).

Students accepted into the program attended a mandatory orientation. The orientation provided a chance for the faculty and advisor to communicate expectations before classes began. Students and faculty used this time to begin relationship building and set the tone for the year. This approach aligns well with the CCCSE (2012) recommendation for an orientation and registration before classes begin. While the

activities differed from other orientations, all students from the institution are required to attend an orientation and register before classes begin. Thus, this component of the first-year program minimally impacted students and the author did not include it as an intervention.

The main intervention of the first-year program involved the creation of a learning community. This community lasted the duration of the program, and the other interventions supported it. Common assignments and activities linked the courses together to create the basis of the learning community. A strong research foundation exists for the efficacy of this intervention, which will be explored in the Literature Review. To prepare, faculty attended a six-week training during which they formed their own professional learning community. This assisted the instructors understanding of the elements needed to create learning communities in the program. In addition, pairs of professors worked on integrated assignments that would be completed for each pairs' classes. Also, an expectation of the program was that instructors would sit in the other instructor's class at least 50% of the time. Table 1 shows the pairings created within the program. Learning communities are considered a high-impact practice by the CCCSE (2012) and the institution (institution document, 2015). Evidence to support that this type of learning community works with students is documented throughout the literature. Finally, faculty chose a theme that connected experiential learning and assignments through the year.

After the summer training, professors were supported in implementing their integrated assignments, activities, and overarching theme by a faculty mentor. The

faculty mentor met with the instructors once a month to help them implement their merged lessons, facilitate discussions regarding retention strategies, and troubleshoot issues experienced by the faculty. The administration provided continuing training throughout the year to ensure important benchmarks were being met, and faculty had times when they could all assemble for work sessions.

Table 1

List of Class Pairings by Semester for the First-Year Program

| Term | Pair 1 | Pair 2 |
| --- | --- | --- |
| Fall | Intermediate Algebra | English Comp I |
| | Student Success Course | Intro to Humanities |
| Spring | College Algebra | English Comp II |
| | Speech | Enlightenment/Romanticism |
| Summer | Business Calculus | |
| | Economics | |

Another component of the first-year program was experiential learning. Faculty organized these activities to connect with the theme; then each instructor volunteered to lead one to two events during the year. All students who participated in the program were informed about the commitment at orientation and expected to attend. Outside-the-classroom learning took two forms for staff and students: co-curricular activities and service learning. The co-curricular activities were focused on supporting student

learning. Activities included workshops that developed skills students need to succeed. These activities were scheduled three times a semester, about once a month, during a time all students could attend. Second, the service-learning projects focused on students using their skills to solve problems within the community. These off-campus trips occurred at most, once a semester. Also, the institution holds many events that are a natural fit into the curriculum. Faculty could have leveraged the existing institutional events to either reduce logistical work or utilize resources otherwise unavailable. All these different activities increased contact with faculty and strengthened engagement with the institution, key factors to success as identified by CCCSE (2012) and Astin (1984).

To support success in the learning community, proactive advising formed the basis of the early alert and intervention strategy. The CCCSE (2012) identified early alert and intervention as a high-impact practice. They report that while faculty will contact students about poor performance, few institutions have mechanisms for reporting those academic difficulties to the advising office. Yet, research by Schwebel, Walburn, Klyce, and Jerrolds (2012), Earl (1988), and Glennen (1975) indicates that proactively contacting students when they start to struggle dramatically improves student achievement. Therefore, the faculty contacted the assigned advisor when students began to struggle. The advisor communicated with the students to target resources, services, or skills needed to produce success. Additionally, the advisor registered the students for their classes in the next semester. This important function increased in value when students were not successful and needed to navigate new

rules and requirements. Consequently, many students not retained in the first-year

program persisted at the institution due to this added layer advising (personal

communication, January 2017). The workflow for the semester is illustrated in *Figure 2*.

| Recruit | Monitor | Register |
|---------|---------|----------|
| •Inform at orientations<br>•Encourage to apply<br>•Follow-up with acceptance or not qualified | •Commincate with faculty<br>•Advise on resources<br>•Grow academic and life-skills | •If successful for next semester in program<br>•If unsuccessful for a new plan created with student |
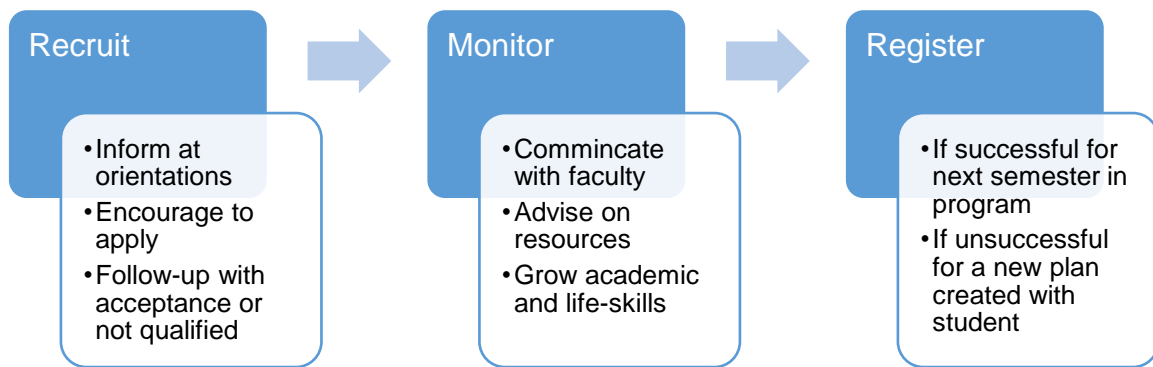
*Figure 2*. Proactive Advising Workflow for Fall Semester.

Another component of the first-year program was experiential learning. During

the academic year, outside-the-classroom learning takes two forms: co-curricular

activities and service learning. First, co-curricular activities were focused on supporting

student learning. Activities included workshops that developed skills students need to

succeed. These activities were scheduled three times a semester or about once a

month. Second, the service-learning projects focused on students using their skills to

solve problems within the community. Faculty organized these activities to connect with

the theme throughout the year. Then, each faculty member volunteered to lead one to

two events during the year. Also, the institution holds many events that are a natural fit

with the curriculum. In this way, the faculty leveraged the existing institutional events to

either reduce logistical work or utilize resources otherwise unavailable. These activities

increased contact with faculty and strengthened engagement with the institution, key

factors to success as identified by CCCSE (2012) and Astin (1984).

The SSC stands as the last intervention included by the author. While the semester-long course is required for all incoming students, the first-year program course was a unique experience. All SSCs offered develop students' academic and other skills that will increase their chances for success. All courses also include co-curricular activities, but standard courses all do the same activities. However, in the first-year program, the SSC was paired with a mathematics course. This meant joint assignments and the integration of specific skills needed to be successful in a mathematics course changed the course from what is normally experienced. Examples of some changes might have included learning to read a mathematics textbook and decoding word problems. The SSC in the first-year program also had the freedom to do any co-curricular or service-learning project that supported the learning community. When juxtaposing the standard course with the first-year program course, it is clear the courses are sufficiently different to warrant being included among the interventions. Finally, the SSC aligns with CCCSE (2012) recommendations and the institution's own work into what improves student achievement (internal document, 2015).

While literature exists regarding the effectiveness of each individual intervention, little published research focuses on determining the outcome of using several high-impact practices on student achievement. Is there a potential multiplier effect in the first-year program's multiple interventions? This study seeks to answer that question.

<u>Definitions of Terms</u>

*First generation in college.* This study will use the definition of neither parent has completed a bachelor's degree.

*Persistence.* The institution defines persistence as remaining enrolled in the college from one term to the next (personal communication, September 2016).

*Retention.* This is defined as remaining in the program from one semester to the next. This is the desired outcome of the program.

*Proactive advising.* This term replaces intrusive advising in recent literature. This is advising where faculty communicate with the advising office regarding students' not succeeding (CCCSE, 2012). It can also be an institutional practice of required meetings by the student with their advisor at specified intervals (Donaldson, McKinney, Lee, & Pino, 2016).

*Covariate.* An independent variable that has the potential to affect the outcome of a study.

*Randomized Control Trial (RCT).* The treatment is assigned by randomization. The result is an unbiased estimate of the average treatment effect (Austin, 2011).

*Quasi-Experimental Design.* The treatment is not assigned at random. The control group is matched as closely as possible to the treatment group. This allows for causal analysis that is typically not possible without random assignment.

# CHAPTER TWO: LITERATURE REVIEW

<u>Test of Theory</u>

In 1984, Astin put forward a student development theory based on student involvement for use by researchers, college faculty, and administrators to help them design more effective learning environments. His general theory directs attention away from subject matter and technique and toward the motivation and behavior of the student. The theory postulates that the more a student is involved with the academic and social life of the college, the more likely the student is to achieve academically and persist in college. He emphasizes the specific importance of the last two of five basic propositions of his theory:

> 4. The amount of student learning and personal development associated with any educational program is directly proportional to the quality and quantity of student involvement in that program.

> 5. The effectiveness of any educational policy or practice is directly related to the capacity of that policy or practice to increase student involvement (Astin, 1984, p. 519).

Astin's theory provides a good framework to look at the first-year program as a solution to student persistence and achievement. One can infer from his theory that applying several interventions increases the engagement of the student, potentially yielding even better results. Whereas Astin's theory does not directly state the need for multiple interventions, the CCCSE, in its report on high-impact practices, states clearly that "multiple practices must work in concert to generate significant change" (2012, p.

29). The organization encourages colleges to adopt many of what it deems high-impact

practices. Those practices, summarized in *Figure 3*, included in the first-year program

are (1) registration before classes begin, (2) orientation, (3) SSC, (4) learning

communities, (5) alert and intervention which can be implemented through proactive

advising, and (6) experiential learning beyond the classroom (CCCSE, 2012). However,

all students within the institution are required to register before classes and attend

orientation. As a result, the major interventions unique to the first-year program are

limited to the SSC, learning communities, proactive advising, and experiential learning

beyond the classroom. Elias and Drea (2013) have also called for multiple approaches

to ensure learning with a variety of students. Thimblin (2015) notes that while SSCs,

orientation, and required advising lead to improved student achievement, these

programs have been implemented only to varying degrees at the community college

level (p. 10).
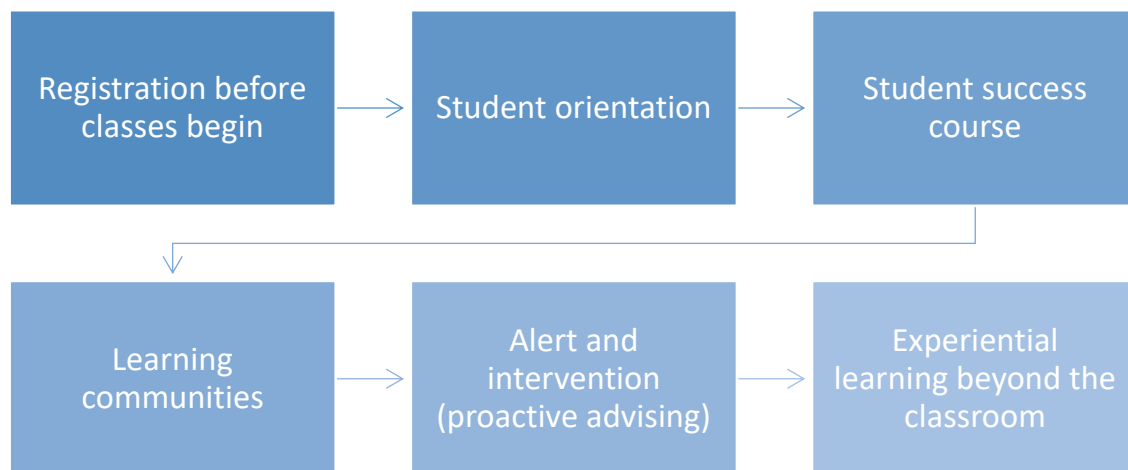


*Figure 3.* Interventions Incorporated in the First-Year Program.

The author searched through the literature to determine whether published research into multiple interventions at the community college level existed. Specifically, the author intended to determine whether community colleges have tried more than two intervention strategies with first-year students. In an effort to be complete, varying terms were searched in EBSCO Host, available through the state university library system. Table 2 summarizes the search results from search terms used to find literature related to multiple interventions.

Table 2

*Results of Search Terms Used to Find Literature Related to Multiple Interventions*

| Search terms | # of search results |
| --- | --- |
| "learning communities" and "intrusive advising" | 0 |
| "college success" and "multiple interventions" | 0 |
| "learning communities" and "freshman experience" | 5 |
| "learning communities" and "student success course" | 5 |
| college success "multiple interventions" | 9 |
| "learning communities" and cocurricular activities | 30 |
| College graduation rates multiple interventions | 39 |
| "student achievement" college multiple interventions | 91 |
| "learning communities" and "experiential learning" | 242 |

While many of the search terms provided zero matches, a few of the search terms resulted in published findings needing analysis. First, the author analyzed

abstracts to determine if the item met the search criteria. When the abstract appeared to meet the criteria, then the full text was analyzed. In the end, the searches revealed one published research article regarding the use of multiple interventions to improve student achievement at community colleges.

The one study that matched the search criteria included three interventions with first-year students at a community college. Butler and Christofili (2014) published a case study conducted at Portland Community College. First, the authors created a learning community of four linked classes, with one class being an SSC. Initially, the study used those interventions to incorporate project-based learning (PBL) into the curriculum of developmental students to determine if it increased student success. The first two semesters of the study did not yield positive results. The implementation of PBL produced dissatisfaction in both students and faculty. Consequently, in the third semester, experiential learning outside the classroom was added in the form of a service-learning project to integrate PBL better. Additionally, the project included a teacher "who serves as a mentor and advisor and who provides wrap around support" (p. 640). The researchers found the modified program improved implementation of PBL and satisfaction of the students in the third and fourth semesters. Even so, success for the case study was focused more on affective domains such as life-long learning and coping with stress. One comment made about persistence related only to previous semesters of the program and not similar students from around the college. Thus, the findings omit traditional measures of student achievement: credits earned and GPA. So, while the program is a match in terms of institution type and interventions used, it is

difficult to determine how successful it was compared to a matched group of students who did not experience the program. However, realizing that the program took three semesters and several changes to achieve its goals encourages others not to discard new programs too quickly.

<center>Multiple Interventions</center>

Residential learning communities (RLCs) can use multiple approaches to help improve student achievement. However, students attending universities and living on campus differ in key ways from commuter college students (Astin, 1984). Also, the literature search revealed some published research from community colleges using two interventions. Therefore, in the following section research into RLC that use multiple interventions are discussed. Following that, a section on literature findings that share qualities with the first-year program are explored to analyze their impact.

<center>Residential Learning Communities: What Can We Learn?</center>

When investigating the literature for programs that use multiple strategies, search results appear with RLCs. Johnson and Romanoff (1999) studied the inaugural year of such a program. Components of the program included interdisciplinary learning communities, faculty mentoring/advising, and experiential learning outside the classroom. These components are similar to the first-year program and are high-impact practices according to the CCCSE (2012). Johnson and Romanoff evaluated the program with a matched control group from the university at large. The students were matched by important covariates including age, gender, enrollment status, and SAT scores. The article does not explicitly state if the researchers used propensity score

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matching, but it does state the matched control group was 100 students. Students in the RLC reported feeling more a part of a community, treated with more respect, and more encouraged by faculty than the control matched group. However, the analyses of GPAs and credits earned were not greater to a statistically significant degree. However, generalization of the success of the program to commuter students should be considered carefully. University students and residential students vary in their academic success versus those attending community colleges and commuting (Astin, 1997; Pike, 1997; Shapiro et al. 2014). Even so, its methodology, variables, length of time, and evaluation of a new program are comparable to the first-year program.

Pike (1997) did research on RLCs at University of Missouri, Columbia, specifically freshman interest groups (FIGs). The study drew from Astin's theory of student development to look for the differences in academic outcomes in students in FIGs versus those who were simply residential students during their first year of college. Pike's research is somewhat unique in the literature due to looking at whether the RLC directly impacted the students' experiences or it was an indirect effect. He was not convinced that there was a direct link due to mixed results in the literature at the time. Study participants were 72% female and 11% minority and included only those with complete data. All students with missing data were omitted from the study. The method of analysis included four background variables to help control for differences in students: gender, minority status, ACT score, and high school percentile rank (p. 5). These variables show associations with differing levels of academic achievement (Astin, 1997). Data were analyzed using a variety of methods to look for differences, direct

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effects, and indirect effects. The most important analysis for determining effects were two-group path analysis models run under diverse assumptions. While Rosenbaum and Rubin (1983) had published their propensity score method to control for differences, it was not commonly used in education during that time (Frye, 2014; Ripley, 2015). Results discovered an effect size of .27 standard deviation increase in gains in general education for the FIGs over the traditional residence students. Gains in general education were derived from six items on the College Student Experiences Questionnaire and not GPA or credits earned by students. However, the structural equations found that the increase in gains in general education was indirect. What the FIGs had a significant direct effect on was involvement in college activities and interaction with faculty and peers. Therefore, Pike's study concludes that learning communities lead naturally to more involvement by the students and that involvement impacts achievement. He cautions that the results may be generalizable to few other institutions given the backgrounds of the study participants. Additional limitations stem from the fact that data were from a self-reporting questionnaire and not GPA or credits-earned data.

<center>Other Programs Utilizing Multiple Interventions</center>

Sawyers (2013) analyzed a retention program at Florida International University, a public research institution, and found that engagement with the college was a predictor of retention. In this quasi-experimental design, the students in the retention program had a statistically significant difference over the control group in a logistic analysis. Major components of the retention program included peer tutoring,

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supplemental instruction, academic advising, and early-alert intervention. While only the advising and early-alert interventions are a part of the first-year program, this again shows leveraging several interventions produced improved student outcomes. Also of note, the result is from a college in the same region possibly sharing similar demographics. Yet, the results may not generalize to community college students.

The CCCSE has extensively researched what improves student outcomes at the community college level (n.d.). Established in 2001 at the University of Texas at Austin, the center provides survey research, focus group work, and other services to community colleges desiring to improve educational outcomes. The CCCSE's surveys have reached more than 6.5 million students and include the majority of public two-year institutions. The CCCSE (2012) reported on several practices that showed meaningful improvement in persistence: orientation, first-year experience, SSC, learning community, and experiential learning outside the classroom. This was a long study that encompassed initiatives like *Achieving the Dream* and *College by Design* spread across 22 different community colleges. The rallying cry of the paper is that community colleges, especially those that have already been a part of the work, need to implement these interventions at scale.

Finally, Mayer et al. (2014) looked at the three best-performing colleges from the *Achieving the Dream* initiative. The stated goal of *Achieving the Dream* included implementing multiple reforms among targeted groups of students with the intent of expanding the reforms across the institution (Mayer et al., 2014). A third of those initiatives targeted first-year students to improve their achievement, similar to the first-

year program. One of the higher performing colleges used learning communities, often in the context of a SSC paired with a developmental course. This incorporates two of the intervention strategies of the first-year program under study. Furthermore, the college was a large southern college, similar in size and in the same region as the institution of the study. Therefore, while none of the high-performing colleges used more than two intervention strategies, it does demonstrate that leveraging multiple strategies can improve student performance specifically with community college students.

Single Intervention Analysis

The previous sections focused on part of the limited literature on multiple interventions and how the analysis was carried out. What follows are examples of programs that use individual interventions to improve student achievement among college students. As much as possible, programs that are comparable to the first-year program are examined for each of the four major interventions. Additionally, special attention is given to covariates, analysis methods, and outcome variables. This was done to provide research support for the methods of this dissertation.

Main Intervention: Learning Communities

*What Are Learning Communities?*

Love has researched learning communities since 1994, publishing articles with Tinto, contributing chapters to books, and writing her own book on the subject. She holds a leadership position with the Atlantic Center for Learning Communities based at Wagner College focusing on learner-centered strategies. Love traces the development of learning communities in "The Growth and Current State of Learning Communities in

Higher Education" (2012) and finds the meaning has changed over the decades. Consequently, she defines a learning community in the following way: "intentional restructuring of the curriculum and student course-taking patterns to emphasize an interdisciplinary focus with attention paid to students' academic and social development" (p. 7). Similarly, Weiss, Visher, Weissman, and Wathington define a learning community as "the coenrollment of a cohort of students into two or more courses. Typically, the curricula of these courses are intentionally linked or integrated, sometimes around a theme" (2015, p. 521). This is the major intervention of the first-year program with all students enrolled in the same classes based on a single theme. The students, faculty, and advisors are all organized in a way that support the creation of a community of learners, according to Love (2012). She asserts that the learning community amplifies the effects of other interventions. Accordingly, all the other interventions of the first-year program support the learning community (see *Figure 4*).
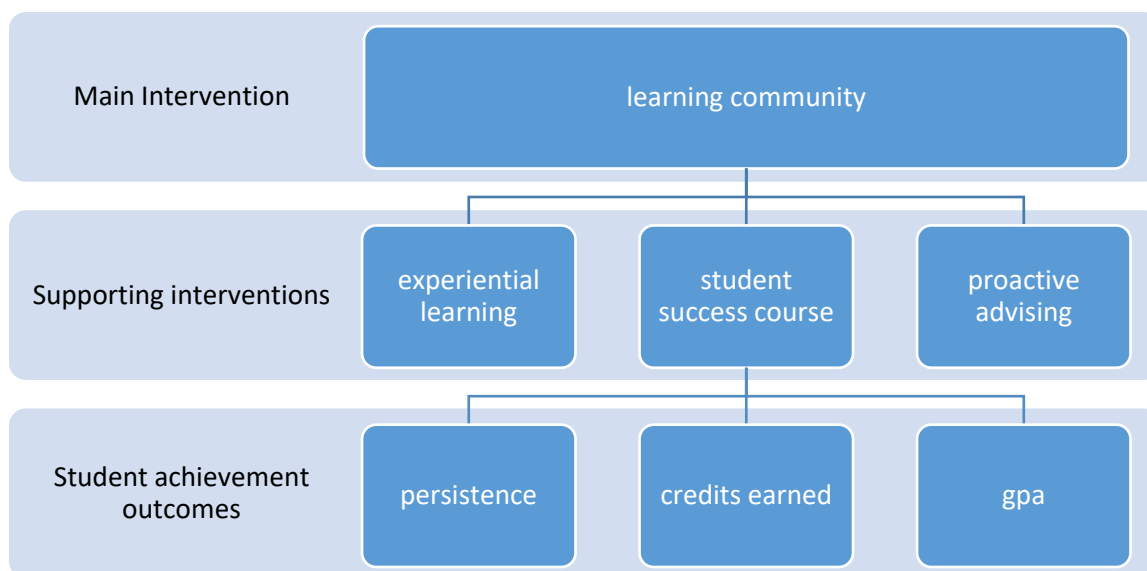


*Figure 4.* Interventions and Outcomes Diagram.

One specific intervention mentioned by Love in conjunction with learning communities is service learning, a type of experiential learning and a supporting component. Consequently, the combined search terms of learning communities and service learning yielded the most published papers (Table 2). The literature then suggests that at least these two interventions create an improved effect exists.

Love (2012) finds that most learning communities improve student outcomes. Love writes "specifically, small cohorts of students in the LC [Learning Community] taking courses together with advising by one of the LC faculty achieved higher-grade point averages (GPAs) and one-year retention rates than the non-LC control group" (p.11). The interventions and assessment reflect the setup of the first-year program and the intended ways to evaluate it. Additionally, Taylor, Moore, MacGregor, and Lindblad (2003) found that when researchers examined learning communities, they found positive results in retention and academic success regardless of methodology or sample size. Even though most researchers agree on their benefits, learning communities can take time to generate meaningful differences and, therefore, should be tracked beyond the initial semester. Taylor et al. (2003) caution against too many expectations being placed on first-semester differences. Yet, this is a strength of the first-year program because it extends through three semesters.

One way colleges try to improve student outcomes is through developing learning communities (Love, 2012). The framework of Love's review was to use Astin's theory of student involvement. She uses the theory to acknowledge three important ways that learning communities contribute to student learning and development: the

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student's peer group, frequent interaction with faculty, and the student's being actively engaged in learning as measured by expending time and effort (Love, 2012, p. 6).

Through learning communities, we observe that when students interact with their peers and faculty, they are more likely to be successful and integrate into the institution (Tinto, 1999). Nevertheless, Elias and Drea (2013) lament that college has become a vehicle to a professional career rather than a means of discovery. Students who commute to class have many obligations that take their focus away from college life (Tinto, Goodsell-Love, & Russo, 1993). So, students may not join study groups or clubs or even want to engage in group projects. Conversely, Tinto (1999) finds connection is a key to success in college. Therefore, building an authentic learning community hinges on moving students to increased levels of interaction, not simply having them occupy the same classroom.

*Learning Communities at Community Colleges*

Bonet and Walters (2016) investigated learning communities implemented at Kingsborough Community College in New England. Learning communities persist due to the institution's long history of successful programs. Students registered for three to five linked courses; one course was a freshman seminar, which provided additional support from counseling services. Additionally, the communities were limited to 25 students. The cohorts researched mirror the first-year program in terms of interventions used. Also, the Kingsborough faculty received additional training and compensation for participating in the program similar to the first-year program. Because learning community programs began at this community college in 1996, there have been many

evaluations of the programs over the years. Most of the results from longitudinal studies indicate increased persistence and engagement of learning community students over students who took comparable classes.

Bonet and Walters (2016) evaluated the current state of the learning communities at Kingsborough Community College. While several of their research questions involved engagement, the last sought to determine if students in the learning communities showed improved academic performance, persistence, and graduation rates over students in comparable classes not in a learning community. Four classes from the Behavioral Sciences department involved in the learning communities' programs and four classes from the same department not involved participated. This yielded a sample size of 247 students to analyze. The results from that analysis showed statistically significant improvements in grades earned in the classes and decreased absences from the classes versus those in the non-learning community classes. The authors attempted to show that the cause of the rise in grades was due to decreased absences, which in turn was due to increased engagement. Yet, Bonet and Walters did not control for any student characteristics in their analysis. Therefore, that students who choose a program that supports their learning might already be more likely to succeed represents a fair criticism of the findings. Finally, while the authors recognize the limitations of the completed study, they suggest more work should be done in the future due to the positive findings.

Romero (2012) investigated learning communities implemented at a southern California community college. He discovered a gap in the literature on the effectiveness

of learning communities at the community college level. While a few of his research questions revolve around cognitive outcomes, one focuses on increases in student grades due to participation in a learning community. Romero states a number of times in the article that generalizing results from learning communities is difficult due to the varied number of implementations and groups of students. Therefore, he chose to limit his study to a single campus of the community college. A survey was provided to 24,500 qualifying students, and 927 students completed the survey. The sample of students who completed the survey were analyzed against the student population to make sure that it was a representative sample. Romero notes a response bias due to only 1.4% of the sample reporting receiving below a 2.0 college GPA because this percentage is higher than the college as a whole.

Regardless of the issues with the sample, Romero performed a multiple regression analysis on the survey results. He chose learning communities as a predictor variable and the dependent variable was thriving, defined to be the success in academic, intrapersonal, and interpersonal pursuits. Results showed no important difference in college grade attainment between students in need of remediation, indicated by a low high school GPA, who participated in learning communities and those not deemed to need remediation. Another way, developmental students in a learning community earned grades on par with college ready students. This is a particularly relevant result because high school GPA was a predictor of college success. The regression analysis showed high school GPA was a significant contributor to thriving ($p < .023$). Even so, when the regression controlled for relevant predictors, learning

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communities did not make a meaningful difference in thriving. The results of Romero's investigation into learning communities show that they can support students who are at-risk, but generalizing the results reduced the effect. Yet, Romero's analysis lacked the outcomes of persistence or GPA between learning community students and the other students in the study, leaving the impact on those variables unknown.

The next study looks at learning communities across several institutions. Weiss et al. (2015) undertook the challenge of creating an experiment to examine the effectiveness of learning communities at six large community colleges across the country. The authors claim theirs is one of the largest randomized trials in higher education with a sample size of 7,000 students (abstract). The students qualified for the study due to being below cut scores on college readiness assessments. The randomizing effect was not perfect, with 29% of those assigned to a learning community not enrolled by the add/drop deadline. The authors regarded those students as intent-to-treat and estimated the effect of offering learning communities (pp. 523-524). When probing the demographic make-up of the participants, samples varied across institutions but no differences were found between treatment and control groups. This justified not only a collective average, but the individual campus impacts being assessed. Weiss et al. concede that the implementation of the treatment was imperfect due to restrictions across the colleges. While the authors found that all classes were co-enrolled and some level of cooperation was achieved by faculty, the integration piece proved difficult to obtain at different sites even to the end of the research study.

The researchers focused credits earned as the key outcome because accumulating credits demonstrated students were persisting in college and maintaining at least a 2.0 GPA. The main results concentrated on the intent to treat every individual assigned to a learning community regardless of enrollment. Additionally, to obtain a better estimate of the actual impact of learning communities, results for those who were enrolled in at least one course at the end of add/drop were broken out separately and analyzed. This increased the participation in a learning community from 71% to 84% of all students assigned. Nevertheless, students assigned to the learning community courses earned on average .52 more credits by the end of the first semester regardless of the group used, those assigned or registered in the first week. This advantage held constant for the next three semesters. Finally, the researchers found notable differences in credits earned between the six institutions. This indicated that the degree of implementation of learning communities strongly influenced student achievement.

The authors list many limitations for the study. First, not every student assigned to the learning communities enrolled; thus, the results obtained did not measure the true treatment effect. In the end, Wiess et al. ascribed a small positive effect on student achievement due to being in a developmental learning community. Furthermore, they cautioned that while a randomized study, other limitations created issues to wide generalization. For example, all the institutions implemented the learning communities differently with varied results. Finally, the researchers pointed to the learning communities running for a single semester potentially limited the impact. So, the first-

year program, which runs for three semesters, could produce a more pronounced effect on student achievement than the above study.

In summary, creating a place where students can connect easily with each other is important. Yet, the above research shows that simply putting students into the same classroom is not the way to build a learning community. The first-year program creates an effective learning community by not only having all the students take classes together, but also through an intentional process. That process begins with summer training to develop integrations and learning opportunities outside the classroom. It continues with administrative support through the year and requiring weekly contact between faculty. Finally, the process culminates with co-curricular activities and service-learning projects that deepen the connections among students and faculty.

Supporting Intervention: Experiential Learning Beyond the Classroom

Students might stop pursuing a degree due to a lack of engagement with the college (CCCSE, 2012; Price & Tovar, 2014; Sawyers, 2013). Lewis (2015) found that community college students at the developmental level participated in more activities outside the college like jobs and family obligations than college-prepared students. This lack of engagement with the institution and academic pursuits hurts the developmental students' ability to be successful (Astin, 1984; CCCSE, 2012). Colleges fight this battle every semester with various initiatives to support students (Robbins et. al, 2009). However, the cited research seems to indicate that many students will not take advantage of the offered initiatives.

Love (2012) found a relationship between learning communities and activities outside the classroom. The first-year program takes advantage of this leveraging by incorporating service learning and co-curricular activities each semester. During the planning stages this summer, faculty and staff were concerned that the students might be overwhelmed and scheduled these activities to occur no more than once a month (personal communication, July 2016). Therefore, part of the solution to students' completing their programs is completing these activities. What follows is current research relevant to understanding one intervention in the first-year program: experiential learning outside the classroom.

*Service Learning*

The CCCSE defines experiential learning outside the classroom as "internships, co-op experience, apprenticeships, field experience, clinical assignments, and community-based projects" (2012, p. 22). The CCCSE classifies experiential learning outside the classroom as a high-impact practice, but many students do not experience it during their enrollment. The CCCSE utilizes the Survey of Entering Student Engagement (SENSE), for new to college students, and the Community College Survey of Student Engagement (CCSSE), for credit taking students, to understand student experiences. The national results indicate that 45% of students desire a learning experience outside the classroom, but less than 13% of students say one has been offered in their course work. Taggart and Crisp's (2011) article described service learning as a specific type of experiential learning. In service learning, students participate in some type of community engagement as part of an academic course.

Simons and Cleary (2006) defined service learning as applying theory to real-world problems such that the project connects to learning objectives in the class. The following are examples of service learning research conducted at community colleges, which give insight into how this intervention might contribute to student achievement in the first-year program.

In the study by Berson and Younkin (1998), comparable classes were taught with a 20-hour service learning component (experimental group) and without the service-learning requirement (control group). The study was conducted within an institution similar to the institution of this dissertation, a large southern community college. English, history, and sociology courses were used, which are comparable to the course load in the first-year program. The same instructor taught both the treatment and control groups and administered identical examinations. While the students were not matched, an analysis of reading ability, English ability, ethnicity, and gender exposed no noteworthy differences between the experimental group and control group. However, the results at the end of the term revealed significant differences in grades and attendance.

Hollis (2002) implemented a comparable study in another southern community college. She was the instructor for both courses and kept factors within the courses as similar as possible. The students in both the structured service learning course and the simple community service course were comparable in underclass ratio, percentage of female students, and ethnicity. Hollis reported improved exam scores ($F = 7.85$, $p <$ .001). Nevertheless, she cautioned against generalizations. One reason may be due to

the sample's being 93% Caucasian. This would not be reflective of the diversity of many institutions nor of the institution in this research study.

Hodge, Lewis, Kramer, and Hughes (2001) investigated a program that integrated a service-learning project into a learning community. The institution under study was a large community college in Texas. The participants were younger like the first-year program students, but they were less diverse (82% Caucasian) and more female (58%). Hodge et al. used interviews and focus groups to determine some outcomes, but quantitative data were used to determine retention (completion of the course, not withdrawing) and student achievement. The retention rates in the learning communities with integrated service learning versus similar stand-alone courses offered improved by 13%. A very limited analysis of grades that was presented in the article showed a positive impact. Some of the limitations in the study stem from failing to control for student background characteristics. Students elected to participate in the more involved, more supportive environment offered by the learning communities. Therefore, these students possibly already exhibited different traits and may have been more motivated or capable than those choosing a traditional academic pathway. Nevertheless, the program does prove that learning communities can successfully integrate service learning and potentially have positive student outcomes.

Taggart and Crisp (2011) conducted a review of service learning and its outcomes, specifically in the community college context. They assert that while a body of research demonstrates positive outcomes in four-year institutions, community college students are unique and, therefore, need separate analysis. Again, they look at the

research through the lens of Astin (1984) and others. Their extensive search of the literature revealed 17 studies that focused on community college students who participated in service learning and that evaluated the programs.

Their review showed that four studies used a quasi-experimental design and focused on student success outcomes. Those studies found service learning had a positive effect on grades and retention. The remainder of the reviews (13) are more qualitative in nature and not focused on academic outcomes. However, they show mostly positive changes in students' attitudes and satisfaction. These results are encouraging because Madden (2015) observes that community college students already have many demands upon their time and find it difficult to participate in experiential learning outside the classroom.

Taggart and Crisp (2011) note there are limitations to the studies they included. First, many studies included more than one intervention, making it difficult to determine how much the service-learning component contributed. Love (2012), however, found that service learning was complementary to learning communities and enhanced the effect. Therefore, this seems like less of a limitation for the first-year program. It is the intention of this test of theory to examine the overall impact of multiple interventions to determine if a synergy exists. Second, most of the studies were program evaluations with limited samples that may not be generalizable. This is a concern for the first-year program because it enrolled only 26 students, but positive results indicate service learning can be an effective part of the intervention strategies.

*Co-curricular Activities*

A second type of experiential learning is co-curricular activities. These are designed to have the students interact more with the faculty and the college. There is some confusion within the literature on the definition of a co-curricular activity. Bartkus, Nemelka, Nemelka, and Gardner (2012) define a co-curricular activity as "one that requires a student's participation outside of normal classroom time as a condition for meeting a curricular requirement" (p. 699).

Madden (2015) sees co-curricular activities through the theory of student involvement posed by Astin (1984). The activities cause students to engage with faculty and the college at large, which, the theory hypothesizes, will promote retention. Even so, non-traditional students are reluctant to engage in these activities given their focus on simply passing classes with other competing obligations. Madden makes it clear that bridging this gap is important to reach the student holistically. Nevertheless, her project sought to transform what older students are already doing and connect it to the traditional co-curriculars the college offers. One example compared an athletic event a student organized with athletics participated in through the institution. Incentivizing activities not organized by the college juxtaposed sharply with the theory of student involvement where increasing engagement with the college is the key. However, Tinto (1999) rethought his theory of leaving in later years with respect to older learners. Tinto saw that these students lived in two worlds that must be bridged. Therefore, connecting outside activities with learning might be a mechanism for persistence. In the end, Madden does not look at how participation in this portfolio process, which connected

experiences outside the classroom with academics, affected student achievement or persistence. So, the study leaves questions about the effectiveness of the program.

Elias and Drea (2013) found that the literature shows a link between co-curricular activities and retention. They saw Astin's (1984) theory as the mechanism for the link. They contend that engagement in co-curricular activities enhances a student's intellectual pursuits. Thus, "while the academic curriculum is the main focus, a broader student experience can positively contribute to students' success" (Elias & Drea, 2012, para. 3). The program they analyzed was the Co-Curricular Record (CCR). It is an official document created by the college for students to document all the outside-the-classroom activities in which they participated. The CCR institutionalizes, recognizes, and rewards experiential learning by encouraging student participation. Ironically, the practice started in the United States, but most programs do not exist here today. Instead, Canadian institutions are now developing these programs for their students. However, the researchers did not measure student outcomes from the programs. Their focus was aimed at employer perceptions of the formal transcript of activities (including descriptions of skills/abilities developed) versus the traditional resume with those activities and skills embedded. The employers overwhelmingly preferred the official transcript attached (71%). Nevertheless, the study leaves open the question of what effect co-curriculars have on student persistence and achievement, either directly or indirectly.

Finally, Zehner (2011) did a comprehensive review of student engagement at Purdue. There are two limitations in this study: it is a four-year school and the five

programs don't quite fit the definition of co-curricular being used in this dissertation. Yet, his was the only study discovered in the literature review that quantified the impact of being engaged in co-curricular or extra-curricular activity. His analysis shows that the beta coefficient for high engagement was statistically significant, having a small effect (p. 13) on GPA but a much larger effect on credits earned (p. 14).

This research lends support to the idea that requiring the service-learning project and two or three co-curricular activities each semester could be a solution to increasing retention. Love (2012) and Taggart and Crisp (2011) conclude that these types of activities leverage others to improve academic achievement. The CCCSE (2012) calls experiential learning outside the classroom a high-impact practice. The research detailed in this section shows that these interventions can have a positive effect on student outcomes. Nevertheless, the research is limited when focusing on community colleges. So, the first-year program adds to the body of knowledge measuring the effectiveness of these practices.

Supporting Intervention: Proactive Advising

Light contends that "Good advising is the single most underestimated characteristic of a successful college experience" (2001, p. 81). O'Banion quantifies this statement more forcefully by stating, "Academic advising is the second-most important function in the community college" (1972, p. 43). So, what constitutes good advising? What kinds of advising are Light and O'Banion referring to that makes the difference in students?

*What Is Proactive Advising?*

Proactive advising (formerly intrusive advising) includes strategies to identify students who are at risk academically, reaching out to those students and advising them of college services or resources that will assist the student in succeeding (Schwebel, Walburn, Klyce, & Jerrolds, 2012). Earl (1988) stated it this way: "Intrusive advising is a direct response to identified academic crisis with a specific program of action. It is a process of identifying students at crisis points and giving them the message, 'You have this problem; here is a help-service.'" (para. 5). Jones (2013) suggests that the proactive advising must be rooted in student developmental theories and treat the student holistically. Both Jones and Schwebel et al. note that some proactive advising requires sessions with students with negative consequences for failing to attend. This follows the CCCSE (2012) findings that early alert and intervention is a high-impact practice. The faculty member contacting the student seems inadequate to improve persistence at institutions. The report shows that while 67% of faculty notify the student directly, less than 27% contact someone else at the college when students start struggling (CCCSE, 2012, p. 20). We should not neglect the traditional role that advising plays in students' being successful. Both Thimblin (2015) and the CCCSE (2012) note that students have too many choices in academic career paths and make fewer favorable choices without guidance.

Glennen (1975) was at the forefront of the proactive counseling movement. He theorized that moving from passive advising to; in his words, "intrusive advising" would increase student retention. The University of Nevada implemented the proactive

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advising model with mandatory meetings. The result over the course of two years was a reduction from 45% attrition to 6% attrition among the freshman class. Glennen also reported that other measures of student achievement increased. This was one of the earliest research studies with this type of advising, but demonstrated that the idea had merit.

Earl was also an early pioneer of advising practices (Jones, 2013). He implemented advising models with second semester freshmen who were on academic probation at Old Dominion University (Earl, 1988). He used a control matched group to measure the effectiveness of the intervention. Propensity score matching was not used, but some covariates were controlled for in the study. The results were positive compared with the control group after three semesters. Yet, success found when using proactive advising on academically struggling students could change with different populations of students.

*How Has Proactive Advising Been Implemented?*

Schwebel et al. (2012) looked at proactive advising at the University of Alabama. This is a large public southern institution, but it has student characteristics different from a community college (Astin, 1984; Shapiro et al., 2014). Advisors from nursing, psychology, and undeclared participated in the study. Schwebel et al. randomly assigned students from the target areas to outreach or no outreach, making it a true experimental design. The researchers state the need for more rigorous evaluation in advising services and hope this study furthers that goal. Every student received the usual contact from the university based on standards of their college. Students in the

outreach program had additional contact every semester based on a predetermined schedule. In the third week, students within the outreach group who had not seen their advisor were sent an email. In the fourth week, if no advising appointment had been made, then a phone call from staff was made. Finally, in the fifth week, if an advising appointment still had not been made, students would receive a phone call from their actual advisor.

The researchers followed students for four years to measure changes in important variables. There were no statistically significant differences in graduation, persistence, credits earned, or GPA. There were significantly more contacts with advising, but this did not seem to lead to improved academic achievement. The authors note that the participants were not at risk when selected and that proactive advising of this type may yield better results with that population. Additionally, students changed majors frequently, and the three areas involved proved a real limitation in this sense because students moved in and out of the treatment group over the course of the four years.

Donaldson, McKinney, Lee, and Pino (2016) contributed to the literature by examining proactive advising at the community college level. They and Thimblin (2015) assert that much of the literature on this topic focuses on four-year institutions, yet differences exist between community college students and university students. The participants are community college students from a large and diverse school in Texas, like the participants in the first-year program. Yet, the study was qualitative and concerned mostly with student experience, unlike the first-year program.

The researchers interviewed 11 students about the intrusive advising process, which included two mandatory meetings at the beginning of the semester and at the midpoint of a student's success class. The advisors used a set of objectives with students to guide each of the sessions. If the students did not attend both meetings, a hold was placed on the students' accounts, preventing them from registering for further coursework. All 11 participants claimed they benefited from the mandatory advising sessions. The perception was that the sessions gave them one point of contact to discuss matters with from the very start of their academic careers. However, students initially held a negative view of the required nature of the advising sessions. The researchers understood the limitations of the study, including the single interview in contrast to a longitudinal study, the small sample size, and the lack of quantitative data to understand changes in persistence and other achievement variables. Regardless, it demonstrated students can view proactive advising positively even when it is required.

Thimblin (2015) looked at advising at a large community college. She used a multi-case study design at community colleges that require advising. Large, multi-campus institutions like the one in this dissertation comprised the community colleges investigated in the study. While she desired to achieve more than one perspective about the problem and solution, varying limitations meant that only two colleges were studied. Thimblin employed different methods to gather the perspectives of students, student services, administration, and faculty. For example, she conducted interviews, made site visits, and reviewed documents during the collection phase. Therefore, the data analysis process was qualitative in nature and followed common conventions. In

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addition, the research questions surrounded how advising was implemented and not how it improved outcomes.

Thimblin (2015) concluded that the institutions' advising lacked meaningful aspects. Each institution struggled to define clear roles and expectations. She expressed concern that "despite the watered-down expectations of advising, the implementation of the requirement still challenged the institutions" (p. 156). So, while this study contributes to the literature on advising at community colleges, it was not designed for the longitudinal evaluation of advising strategies on retention or academic performance that Schwebel et al. (2012) state is needed in advising research. Yet, the study reveals how long and difficult it can be to create meaningful change, an important message for institutions trying to improve.

Kolenovic, Linderman, and Karp (2013) used a longitudinal quantitative approach to evaluate academic advising at The City University of New York (CUNY). While CUNY is a northeastern institution, it is a large, multi-campus, diverse community college. The program at CUNY involved students who were college ready but had potentially taken developmental classes. The students also had to have less than 12 credits earned in college (first-year student) and not be enrolled in any other special programs. Advisors reached out to students who qualified to recruit into the program. The program had the following components:

- Enrolled in at least 12 credit hours

- Scheduled for classes that were in the morning, afternoon, evening, or weekend only. This meant all course timing was very close and freed time for other responsibilities

- Organized by major, so students took classes with other cohort students

- Full-time program staff for advisement and career development

- Twice monthly required advising sessions

- Tuition gap coverage

- Access to textbooks

- Public transport pass to commute to school (pp. 273-274)

The theory underpinning the program espoused a multi-faceted approach to student development and achievement. The three facets were academic momentum, sense of belonging, and timely support services. While the multiple interventions theory is similar to this research, the interventions chosen are very different. Kolenovic et al. used propensity score matching of 1,132 students to evaluate the effectiveness of academic advising at CUNY. The comparison group met the same requirements as the program students, including major. Major was one of the variables determined to be of importance for matching group in the current study as well. Another limiting criterion was the year of admittance; only those students who entered in 2006 were considered for the matched group. The choice of limiting criteria leads to differences in age, income, and other variables (p. 278). Other matching variables included gender, race/ethnicity, age, campus attended, exemption from assessment, financial aid, Pell Grant status (a federal subsidy based on financial need), and TAP grant status (a state

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subsidy based on financial need) as proxies for socio-economic status. The authors report these variables were used in other studies and were similar to the variables in this study.

Kolenovic et al. (2013) followed the students over three years and looked at several different student achievement variables. Comparing an optimum propensity score matched group with the program group that received the interventions, data showed a 12% increase in persistence to a degree. An interesting result from the study was that students who were more academically prepared sought less advising than the at-risk students. As a final thought, Kolenovic et al. cite research that learning communities, SSCs, and some guidance interventions lose effect over time but that the program implemented at CUNY did not seem to suffer from this issue (2013, p. 287).

Supporting Intervention: Student Success Course

*What Is a Student Success Course?*

The CCCSE defines a SSC as a course that will "help students build knowledge and skills essential for success in college, from study and time-management skills to awareness of campus facilities and support services" (2012, p. 15). Others define a SSC as one that develops academic and personal skills, orients students to campus resources, and promotes educational and career planning (Kimbark, Peters, & Richardson, 2017). Hoops, Yu, Burridge, and Wolters (2015) define a SSC as "semester-long course interventions based on principles of SRL [student regulated learning] . . . designed to boost students to higher levels of SRL engagement, grades, and retention" (p. 124). Viewed through the lens of the theory of student involvement,

the SSC can improve the quality and quantity of time students spend on academics (Astin, 1984). SSCs taken in the first semester by the first-year program students improves the quality and quantity of time spent on academics by developing academic and personal skills. This includes time-management skills, finding resources on campus, and fostering lifelong learning. Thus, the SSC possesses the elements described in the definitions and other successful courses.

Kimbark, Peters, and Richardson (2017) state that much of the early research into SSCs comes from four-year institutions with community colleges recently introducing this intervention. The CCCSE reports only 15% of schools require SSCs for all students. Kimbark et al. cite similar findings in their research; while SSCs have a positive impact, few schools are implementing them (p.125). This may be because some studies show no impact on student achievement. Kimbark et al. cite four studies that even after controlling for student background do not seem to improve variables like GPA. Therefore, it seems that the type of course developed and the types of students who experience it impacts retention and GPA (Hoops, Yu, Burridge, & Wolters, 2015). What follows are the results from studies about the effects SSCs like the one experienced in the first-year program have on student outcomes.

*Student Success Courses at Community Colleges*

Kimbark et al (2017) examined the effects of a SSC using the Community College Survey of Student Engagement (CCSSE). The study collected data from a southwest region community college with a diverse population. Participants enrolled in SSCs were matched with students who did not take the course. While the researchers

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referenced propensity scoring in their review of studies, they do not mention it as the method of matching. The researchers simply showed the equality of the two groups based on numerous factors that tend to be associated with student achievement. No significant differences were noted in the purposefully matched groups. Qualitative data were collected and analyzed in standard ways: coding, categorizing, triangulation, etc. Quantitative data were converted to categories so that Chi-squared tests of independence could be used. For example, the researchers converted letter grades of A, B, and C to successful completion while D and F converted to unsuccessful completion. The results showed statistically significant increases ($p < .05$) between the SSC group and non-SSC group for persistence, retention, English success, and mathematics success. Also, large differences existed between the persistence of the SSC group and non-SSC group: 68% vs 56% respectively. Additionally, the SSC group and the non-SSC group showed pronounced differences in mathematics success: 67% vs 30% respectively. Kimbark et al. explained possible reasons that some SSCs do not have positive outcomes in their conclusion. They state "this study revealed that it is not only learning the skills themselves, but how the participants internalized those skills and generalized their usage that truly influenced their decisions to stay in college" (2017, p. 135).

Windham, Rehfuss, Williams, Pugh, and Tincher-Ladner (2014) described the purpose of their post-facto quasi-experiment as determining which characteristics increase community college retention among first-time, full-time community college freshmen enrolled in a SSC. Additionally, while several of the student outcomes were

similar to other programs, such as learning study strategies, setting personal and professional goals, and becoming familiar with campus resources, the integration of student affairs during the course added another intervention. Students qualified for inclusion in the study if they possessed an ACT COMPASS© score ($n = 1740$), which measures college readiness. Also, the researchers chose variables that influence student achievement to reduce bias in the analysis. Hence, data collected about participants included gender, age, ethnicity, socioeconomic status, and enrollment in a SSC. The data provided by the institution contained all needed demographic and academic information but were stripped of all personally identifiable information. Finally, the students' completion of the SSC determined the coded category: successful (letter grade of A, B, or C), unsuccessful (letter grade of D or F), withdrawal (received a W), or non-enrolled (did not take the SSC).

This study provides valuable insight into the first-year program due to its being in the same region and at a comparable institution. Furthermore, it used some common interventions, and it provided analysis with similar methodologies. The researchers determined fall-to-fall persistence using a logistic regression due to the dichotomous dependent variable and mixed levels of measurement for the independent variables. The results from the analysis showed successful completion of the SSC led to significant increases in retention over the other three categories ($p < .001$). Findings revealed students who successfully completed the SSC were 64% more likely to persist to the following fall over those not enrolled in the SSC course. Differences were even greater between those successful in the SSC than those who were unsuccessful or

withdrew. It is worth noting that race/ethnicity ($p = .129$) and financial-aid status ($p = .663$) were not significant predictors of persistence. However, females in the study were 94% more likely to persist than males. The authors recommended more programs that increase male participation at the institution to improve their persistence rates.

The next study is from a large southwestern public research university and was chosen due to its use of propensity score matching (PSM), quantitative analysis, and use of student outcome variables: persistence and GPA (Hoops et al., 2015). Hoops et al. obtained data from the university database at three different times: Spring 2007, Fall 2010, and Fall 2011. The PSM was first matched by gender and ethnicity. Then the group was matched according to earlier academic performance based on ACT, SAT, and prior university GPA. Finally, a third match of age within one year was made. Tests were conducted to ensure the two groups were well matched. The results showed no significant differences between the covariates. The researchers note that the course is not designed for freshmen and is typically taken by students starting their upper division classes. However, because the SSC was offered as an elective, freshmen are part of the sample. This may explain some of the variance in the results.

One result was that retention in the next semester was not significantly different. However, the sample sizes were only $n = 9$ and $n = 26$ respectively, calling into question the power of the test to detect differences. Similarly, no significant results were found for differences in GPA. Significant differences were found in the pre-post analysis of data measuring student regulated learning, which some research shows are a predictor of degree completion. In the end, the researchers caution that while some results were not

significant, many student outcomes were not measured and could have been positively impacted. Additionally, they note the difficulty of improving retention and GPA for the upper division students contained in the samples. This study presented an example of partial success from an implemented SSC.

Jenkins-Guarnieri, Horne, Wallis, Rings, and Vaughan (2015) researched SSCs implemented at a public four-year university in the mountain states. Some of the components included time management, study skills, and increasing commitment to the college. The course involved small class sizes (not defined by the authors), enrollment by major, and a focus on student development instead of a focus on school resources. These components align with the first-year program SSC. More than once, the researchers lament the lack of rigor in evaluating these programs. The researchers called for better methodology echoing the concerns of the CCCSE (2012). The study controlled for gender, ethnicity, educational preparation, and first-generation in college as these are known covariates in the research and would confound an analysis (Astin, 1984, 1997; CCCSE, 2012; Fischer, 2007; Mayer et al., 2014). The logistic regression performed on the data showed the course increased persistence and academic standing among those taking part in the SSC by around two times from non-participants. This finding matches other national institutions that have implemented such courses (Jenkins-Guarnieri et al., 2015).

Ewing-Cooper and Parker (2013) researched freshman orientation courses and stated that students who participate in these courses do better academically and demonstrate more persistence. They researched this at a major southwestern

university. While this study called the course an orientation, SSC is a better description following the definition used by the CCCSE because it included topics such as career advising, communication skills, campus resources, and problem solving (p. 2). The participants were overwhelmingly female (94%), mostly Caucasian (67%), and younger ($M = 19.4$, $SD = 1.6$). These demographics make it hard to generalize to other institutions. The researchers developed a simple 10-item survey to measure perceptions of preparedness and how likely students were to persist toward a degree. The survey instrument was administered in the first week of the class and the last week of the class. T tests run on the pre-post survey data looked for significant differences, and the researchers found the freshman orientation course improved students' perceptions of preparedness and belief they could be successful in college. The researchers believed that this would improve their academics.

However, a mere improvement in perception may not be enough to increase achievement. Rutschow, Cullinan, and Welbeck (2012) evaluated similar courses, and found student success skills such as time management and interest in life-long learning improved, but students' academic achievement did not. Additionally, Hoops et al. (2015) reported changes in student regulated learning but not in persistence at the institution or GPA. Therefore, Rutschow et al. (2012) indicated that a more comprehensive approach was needed to achieve improved student outcomes, which is echoed by the findings of the CCCSE (2012). So, while a SSC can have an impact on students' achievement through many mechanisms, who receives the intervention and how the intervention is implemented make a difference in the results.

Evaluating the Theory

Mayer et al. (2014) conclude that simply instituting reform will not improve student achievement unless the reforms are efficacious. The researchers explain that there is a need for rigorous evaluations of programs to determine which are effectual. Specifically, "rigorous research is needed on the causal aspects of specific interventions that directly affect the experiences of students" (p. 13). Their desire is for institutions to prove that programs work and share them, so that others would benefit.

Therefore, there is a need for methods to measure program outcomes when researchers cannot randomly assign students. Ripley (2015) and Frye (2014) contend that while propensity score matching was created by Rosenbaum and Rubin in 1983, it has seen use only recently in educational settings. In an effort to promote more rigorous analysis of theories and programs, what follows is an explanation of the method and how it is used to assess programs. The hope is that with an improved understanding of the technique, more educational researchers will avail themselves of the tool.

Propensity Score Matching

In educational settings, ethical and logistical questions arise when trying to assign students randomly to interventions. An experiment utilizing random assignment reduces bias and aids in determining the effect of the intervention. However, observational studies of two different groups have serious limitations, including selection bias and other variables impacting the observed differences (Ripley, 2015). Rosenbaum and Rubin (1983) created a statistical tool to overcome this limitation: propensity score matching (PSM). Through their paper, Rosenbaum and Rubin demonstrated that

observational studies mimicked the randomized experiment when using PSM.

Simulating random assignment in an observational study is often referred to as a quasi-experimental design. Through this design, a causal inference can be made with regard to the intervention and measure the real difference between the groups (Austin, 2011; Kim & Steiner, 2016; Rosenbaum and Rubin, 1983).

PSM is accomplished through a four-step process summarized in *Figure 5*. The first-step of the process is measuring all variables that influence the treatment; these variables are called covariates (Rosenbaum & Rubin, 1983). Using the covariates, the researcher can create a balancing score, which is also known as a propensity score. The propensity score then is "the propensity towards exposure to treatment 1 given the observed covariates" (p. 43). The propensity score is the independent variable calculated by a logistic regression of the covariates. The treatment group can be balanced with the control group by matching the propensity scores (Ripley, 2015). Once properly balanced groups are obtained, normal statistical tools can be used to detect differences. The researcher can then determine the average treatment effect in an observational study using this technique (Rosenbaum & Rubin, 1983).

| Step 1: Select covariates | Step 2: Choose matching parameters | Step 3: Check matching quality | Step 4: Evaluate effects between groups |
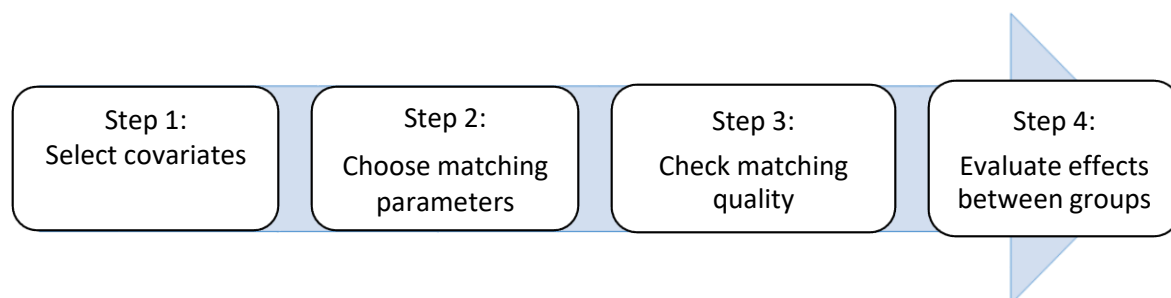
*Figure 5*. PSM Steps.

Rosenbaum and Rubin's (1983) analysis hinged on the selection of covariates. Austin (2011) explains this assumption as the "no unmeasured confounders" condition (p. 403). Ripley (2015) calls this the first and the most crucial step with respect to the analysis. He states that one must explore the literature to determine as many covariates as possible that might influence the treatment effect when using PSM (2015, p. 59). As this is crucial to the analysis, the selection of covariates is discussed in the next section of the literature review in detail.

After the covariates are chosen, the researcher must select the methods by which the matches will be created. Three questions for analysis need to be answered (Ripley, 2015):

1) How close a match will be specified?

2) How many matches per control unit will be specified?

3) Which algorithm will be used to make the matches?

In a perfect world, treatment subjects would be exactly matched with control subjects (Austin, 2011). Even so, this is rarely the case with real data. Therefore, how different the matches can be between subjects must be answered. Austin discusses two choices: without caliper and with caliper (p. 406). With the restriction of the caliper, which is a specified distance, comes the possibility that a treatment subject remains unmatched due to no control subject being a close enough match. This leads to smaller sample sizes, which impede the ability to of researchers to determine the effect of the intervention. Otherwise, regardless of how different the scores, whenever the algorithm finds the closest match, the control subject is paired with the treatment subject. This can

lead to poor matches containing the bias the method seeks to reduce. Austin concludes that there is no consensus on an optimal distance. However, his own research and that of others has pointed to a distance of .2 of the pooled standard deviation of the propensity score because it leads to a reduction of 99% of the bias.

The second question, how many matches per control unit, is related to the type and number of matches. For type of match, the researcher must choose from with or without replacement. If matches are replaced, they are available for other treatment subjects (Austin, 2011). Ripley argues that the choice of replacement strategy has a negligible effect on bias and treatment effect (as cited in Ho et al., 2007). However, Austin finds that increasing the matching from one-to-one to one-to-multiple leads to a reduction in bias and a better estimate of treatment effect. In the method of one-to-many, all subjects within the specified distance are considered matches. This leads to fewer subjects being eliminated from analysis than using a simple one-to-one matching scheme. This larger sample size improves a statistical test's chances of detecting real differences between groups.

The last question relates to the algorithm itself. Austin (2011) compared two types: optimal and greedy. In the optimal algorithm, all potential subjects are searched for the best match to the current treatment subject. In contrast, the greedy algorithm grabs the first subject that is a match for the treatment subject. Austin finds that neither method holds an advantage in reducing bias nor detecting treatment effect. Ripley (2015) describes three types: optimal matching, nearest neighbor, and stratification. Optimal is the process of matching every treated subject with the best control subject. It

previously required advanced coding to implement (Riley, 2015) but SPSS Statistics

and the R plug-in is now capable of optimal matching without coding. Greedy and

nearest neighbor are basically the same approach; both algorithms look for the best

match for the current treated subject without regard for future matching. Stratification is

a unique matching strategy. Rosenbaum and Rubin (1983) describe breaking the

subjects into five strata based upon their scores and matching within the strata. For

example, the uppermost 20% of treatment subjects are matched with the uppermost

20% of control subjects. This method is shown to reduce 90% of bias as long the

distributions of the strata are similar (Ripley, 2015).

As previously noted, not all covariates that impact outcomes can be measured.

Therefore, before any analysis of the two groups can be made, the researcher needs to

understand how well the two groups were matched (Austin, 2011; Ripley, 2015). When

the covariates have been appropriately selected, the propensity score distributions

between the treated and the control will be similar (Austin, 2011, p. 411). If significant

differences exist between the distributions, then bias between the treated and control

may not have been adequately reduced. Both Austin and Ripley recommend using

Cohen's *d* to measure differences. This calculates the standardized differences

between the two means, a common measure in statistics. Austin suggested that $|d| <$

.25 or, more conservatively, $|d| < .1$. If values are within these limits, then the model has

been adequately specified. Austin also recommends looking at graphical methods to

determine the suitableness of comparing the two. SPSS Statistics (Version 24) provides

these graphs and more as the software continually improves. A host of options are available to the researcher with more added all the time.

There are additional considerations to implementing PSM. It works well when the number of participants and matching criteria are small, and the pool of potential matches is large (Kim & Steiner, 2016). The data provided by institutions must include enough control subjects that appropriate pairs can be created. When this is true, it seems logical to use PSM to create a quasi-experimental design to calculate differences as part of a program's evaluation.

## The Choice of Covariates

In PSM, determining the covariates that would most influence the outcome is of utmost importance (Austin, 2011). Astin (1984, 1997) demonstrated that students carry with them important characteristics that affect their success. In many of his studies, significant variables were high school grades and curriculum, parental level of education, and SAT/ACT scores. Porchea, Allen, Robbins, and Phelps (2010) found "numerous studies have shown that prior academic achievement predicts academic performance and persistence in college; high school grades and standardized test scores are often used as a basis for college admissions and placement decisions" (p. 683). Therefore, high school GPA and SAT/ACT scores represent covariates to be included as part of a propensity match when dealing with college students. However, Porchea et al. found that only 25% of the variance in college GPA and retention was due to these two factors.

Fischer (2007) found three factors that seemed to influence college success: minority status, socio-economic status, and first generation in college. Minorities generally start college with lower academic performance. This developmental starting point can lead to lower levels of retention and grades (CCCSE, 2012). Considering these two factors, it makes sense to include ethnicity and socio-economic status as covariates. Fischer (2007) also points out that being first time in college may separate the student from family and friends. If this alienation is not offset by engagement with the college community, then withdrawing from college might occur. This aligns with Tinto's (1975) theory of departing. On the other hand, students with family and friends who have attended college might be more supportive of the student, leading to less alienation and more persistence (Tinto, 1975). Therefore, first time in college status should be included as a covariate.

In addition to the above covariates, there are others to consider. From the CCCSE (2012) and Astin (1984) we know that full-time students tend to have better retention than part-time students. This makes enrollment status a covariate to include in the analysis. The first-year program students were all enrolled full-time. They have also declared business as their major. The literature finds these variables to be predictors of success. For instance, Frye (2014) determined that differences between declaring a four-year goal versus a two-year goal was a covariate. Moreover, Yee (2014) examined the choice of major and discovered that demographic characteristics influenced the choice of major. Consequently, the choice of a business major carries important information about the students and should thus be considered a covariate.

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Lastly, the fall mathematics course in the first-year program is Intermediate Algebra. This course has high enrollment and a low success rate for students at the institution (institution document, 2009). Because all members of the cohort are required to take this course, it contains consequential information about students who sign up for it. In addition, Frye (2014) found completion of a college-level mathematics course to be an important covariate for persistence. Literature and history at the institution indicate Intermediate Algebra is a significant covariate. If the multiple interventions work, then differences should be found between the success of first-year program students and a matched group that did not have the interventions.

# CHAPTER THREE: METHODOLOGY

## Evaluation Plan

The present impact study investigated the factors affecting community college students. Reviewing the literature showed researchers frequently measure persistence, retention, and other student-level factors to determine the impact of interventions on academic achievement. Several authors also called for a rigorous analysis of programs to determine effects, while considerations of reproducibility influenced choices made by the author. Therefore, as described within this chapter, this study employed a quasi-experimental design to reduce bias and increase rigor to model student-level effects. Using data normally collected by the institution assisted reproducibility and minimized ethical issues. PSM controlled for differences between those in the first-year program and those not experiencing the interventions and allowed for causal-comparative analysis. The variables planned from the institution tend to be related to academic retention and achievement in public two-year as shown in the literature review. This chapter details the intent of the author in the planning stages of the study, before data were available.

## Setting

The study was carried out at a public two-year college located in the Southeastern United States. The college had an annual enrollment of over 60,000 students spread across seven campuses the year of the study. The institution also offered 25 different transfer plans to the local university and 33 Associate of Science degrees that lead to careers. It serves a wide range of ethnicities, ages, academic

plans, and socio-economic statuses. The institution continues to lead in different areas, earning awards on a consistent basis.

## Participants

All students who participated in the program were recruited from one campus at the institution during the summer of 2016. Students were eligible and enrolled in the program if they were a declared business major, enrolling on the campus implementing the program, and if they had not earned credit in any classes scheduled (see Table 1). The first 26 students to apply were accepted, while other applicants were placed on a waitlist. All of the students ($n = 26$) who started classes in the program in the fall of 2016 were included in the study.

Of the 26 participants, there were 18 males and eight females. The ethnicities break out in the following way: eight Hispanic, seven Black/African American, 10 White Non-Hispanic, and one Unknown. Students reported as first generation in college numbered nine, with the remaining having at least one parent with a degree past high school. Out of all the students, only six took the SAT, and three of those students also took the ACT. The mean for the SAT Math was 382, with a range from 240 to 480. The mean SAT Verbal was 405, with a range from 240 to 560. High school GPA records were transcribed for 17 of the students with a mean GPA of 2.89, with a range from 2.31 to 3.96. Finally, almost half of the participants (11) qualified for Pell Grants. This group of participants then carry with them many of the characteristics that Astin (1997) found put them at risk for leaving higher education.

## Data Collection

UCF's Institutional Review Board approved the collection of non-identified student data (see APPENDIX). The institution provided the data stripped of all personal identifiers. The data file provided the needed information for the propensity score match after the Spring 2016 semester. Table 3 presents the final list. Students reported gender, ethnicity, and whether parents had attended college during the admission process. The remaining data were compiled from student records.

Table 3

*Summary of All Variables Provided by the Institution*

| Independent | | Dependent |
|---|---|---|
| Cohort/Non-Cohort | Age | Cumulative Credits Earned Fall |
| First Generation in College[*] | ACT Math | Cumulative Credits Earned Spring |
| First Time in College | ACT Writing | Cumulative GPA Fall |
| First Time at Institution | ACT Reading | Cumulative GPA Spring |
| Enrollment Status | SAT Math | |
| Original Degree Goal | SAT Writing | |
| Pell Status | SAT Verbal | |
| Ethnicity[*] | High School GPA | |
| Gender[*] | | |

[*]self-identified during admission process

Participants were identified as *Cohort* and the remaining students were identified as *Non-Cohort* for making matches. On three separate occasions, the person organizing the data contacted the author to ensure all the needed data were included. Those conversations led to variables chosen that matched the important covariates as closely as possible for this study and available from the institution.

## Methods

### Propensity Score Method

Data provided by the Institutional Research Office were analyzed by SPSS Statistics (Version 24) with the PS Matching plugin to find propensity matches. PS Matching looks for as close as possible a match among the control students to the subjects in the program. The output is a group that is like the program students, except the group was not part of the program. This, in effect, is the control group with which to compare outcomes. The code also provides the propensity score from 0 to 1, which shows how closely the control group matches the program group. This provides insight into how well matched the two groups are along the variables (Austin, 2011). Three limiting variables were chosen based on a review of the literature and from the available college records. Those variables were campus location and declared major. This ensured bettering matching by reducing bias that might exist between campus locations and declared major. Also, students enrolled in Intermediate Algebra was used as a constraint. Intermediate Algebra was described as a high enrollment, low pass rate class by the institution (personal communication, August 19, 2016). The remaining

variables chosen for the match were the intersection of literature and those available

from the institution. They are listed in Table 4.

Table 4

*Propensity Match Variables Used to Select Control Group*

| Variable | Level of Measurement | Description |
| --- | --- | --- |
| Ethnicity[*] | Nominal | ethnicity selected at admission to the college (Caucasian, African-American, Hispanic, Other/Not Available) |
| Gender* | Nominal | gender selected at admission to the college (Male, Female) |
| Age | Ratio | age calculated from birthdate given the college (range from 18 to 56) |
| First Generation in College* | Nominal | student indicated that neither parent went to college at admission (Yes = 1, No = 0) |
| FTIC | Nominal | student was not previously enrolled in higher education (Yes = 1, No = 0) |
| Enrollment Status | Ordinal | based on the number of credit hours taken in the Fall 2016 Semester (FT = Full-time, > 11 hours; PT = Part-time, < 12 hours) |
| SES | Ordinal | Pell Grant status was used as a proxy for socio-economic status (Pell received = 1, No Pell = 0) |
| College Entrance Exam Scores | Continuous | SAT scores were converted to ACT scores. (range from 11 to 27) |
| High School GPA | Continuous | Cumulative high school GPA as transcribed from records. (range from 1.5 to 4.0) |

[*]self-identified during admission process

Tests of Significance

Once a matched group has been found, standard tests to find statistical significance can be used to determine if the program reached its intended outcomes as stated in the research questions. The CCCSE used a level of significance of .10 for their analysis. They justified this by noting that the measure of outcome was separated by time from the intervention. This liberal level of significance was used in this study.

*Research Question 1*

To determine if there exists a significant difference between the persistence rates of the cohort and the matched group, a $\chi^2$ test of independence was used. The provided data coded a Fall 2016 student enrolled in Spring 2017 with a yes. In the same way, Spring 2017 students enrolled in Summer 2017 were coded with a yes. Evaluation of the groups was done in SAS (Version 9.04) using the PROC FREQ command with the CHISQ and CMH options. The CMH option provides information on the odds ratio to determine the effect size of the first-year program on persistence.

*Research Question 2*

To determine if there exists a significant difference between the GPA of the cohort and the matched group, paired t-tests were used. Data provided by the institution included cumulative GPA for the end of Fall 2016 and end of Spring 2017 terms. The evaluation between the two groups was done in SAS (Version 9.04) using the PROC TTEST command. The confidence interval reported provides information on the

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expected difference between the two groups at the 90% level and Cohen's *d* will determine effect size.

<p align="center">*Research Question 3*</p>

To determine if there exists a significant difference in the credits earned between the cohort and the matched group, paired t-tests were used. Data provided by the institution recorded the cumulative number of credits earned by the student at the end of Fall 2016 and Spring 2017 terms. The evaluation between the two groups was done in SAS (Version 9.04) using the PROC TTEST command. The confidence interval reported provides information on the expected difference between the two groups at the 90% level and Cohen's *d* will determine effect size.

<p align="center">Multiple Regression Analysis</p>

Because these data contain both continuous and categorical data, and the outcome for credits earned is continuous, a multiple regression model was chosen to determine the level of impact the first-year program had on students' academic progress through the first two semesters. This model allows researchers to control for covariates and determine the effect size of participation in the first-year program.

To do this, the author created a new variable – treatment effect. This ordinal variable measures how long a student was in the program. The longer a student participates, the larger the treatment effect. The new variable coding is explained in Table 5. The coding stops after the spring semester due to data being unavailable for the summer semester at the time of the dissertation.

<p align="center">67</p>

The multiple regression model utilizes the same covariates used for matching to avoid bias in the estimate of the treatment effect. Yet, the independent variable is now credits earned by the end of the spring semester. This variable is a proxy for both persistence and academic success. If credits earned accumulate, then the student has continued to re-enroll in classes. Additionally, more credits occur only upon successfully passing courses. Therefore, credits earned is a good choice to determine the effect of the program. Weiss et al. (2015) used this variable to measure student achievement in their study. Again, the treatment variable explained in Table 5 is being added into the model now, not to match but to measure its impact, and the model used all other covariates as detailed in Table 4.

Table 5

*Treatment Variable for Multiple Linear Regression*

| Variable Name | Variable Type | Description/Coding |
| --- | --- | --- |
| Treatment | Ordinal | 0 = did not participate, control group |
| | | 1 = not retained through end of fall |
| | | 2 = retained only through end of fall |
| | | 3 = not retained through end of spring |
| | | 4 = retained at least through end of spring |

Table 6

*Independent Variable for Multiple Regression Model*

| Variable Name | Variable Type | Description/Coding |
|---|---|---|
| Total Credits Earned | Continuous | The number of credit hours accumulated by the student from fall to spring. (range = 0 to 36 hours) |

*The Exploratory Question*

To determine the measured impact of the program on student persistence, a multiple linear regression model was built from all the students with high school GPAs in the database provided, not just those in the propensity score matched groups. All the important covariates were retained, but the lager sample increased the power of the model to detect differences that exist. The $R^2$ values and standardized β weights produced by the model were used to determine effect sizes of the variables with the key variable being treatment. The model was constructed and evaluated with the PROC REG function in SAS (Version 9.04).

<u>Summary</u>

This study was a quasi-experimental design that used PSM to create matched pairs of students. Matching variables were selected based upon a review of the literature and data available from the institution. Then, the institution provided the author the requested data without identifying information to protect the students. In the next chapter, the analysis involved in creating the matched pairs is described, followed by

evaluation of the research questions. The questions were focused on persistence, GPA, and credits earned.

## CHAPTER FOUR: FINDINGS

### Preparing the Data

The institution complied the data and provided it in the prescribed format after Spring 2017 grades were recorded and summer classes had begun. The timing helped to ensure as complete a data set as possible was used. The original data set provided the required characteristics and academic achievements for 21 cohort students and 349 control students. The number of control students provided exceeded what was needed for good matching. However, five cohort students were missing from the data set. No satisfactory explanation was discovered; therefore, all analysis was completed using only what was provided.

As covariate balance is important in PSM, analysis began with tests to determine if there were differences between the two groups at the outset. For all the categorical variables, $\chi^2$ tests of independence were conducted. The results of those tests are presented in Table 7. For the two continuous variables, independent t tests were performed.

Additionally, the data received contained only 11% of students with SAT or ACT scores. The PS Matching function in SPSS Statistics (Version 24) will not run with missing data. Typically, analysts run missing value algorithms to fill in gaps, like multiple imputation or expectation maximization. However, the amount of data missing and the categorical nature of most variables made using missing value procedures highly unadvisable. To overcome this limitation without losing an important covariate, the author converted SAT and ACT scores to a dichotomous variable: college-preparatory

exam (yes = 1 and no = 0). This retains valuable information; the student took the exam

potentially to attend a university and appropriately handles the missing values.

Table 7

*Summary of Categorical Differences between Cohort and Full Set of Control Students*

| | Subjects | | |
|---|---|---|---|
| | Treatment | Control | |
| Variable | (n = 21) | (n = 349) | $\chi^2$ |
| Gender | | | |
| Male | 67% | 57% | .788 |
| Female | 33% | 42% | |
| Ethnicity | | | |
| Caucasian | 29% | 38% | 3.345 |
| Hispanic | 33% | 35% | |
| African American | 33% | 20% | |
| Other | 5% | 3% | |
| Enrollment Status | | | |
| Full-Time | 100% | 66% | 10.425*** |
| Part-Time | 0% | 34% | |
| First-Time in College | | | |
| Yes, First Time | 100% | 51% | 19.340*** |
| No, Returning/Transfer | 0% | 49% | |
| Degree Plan | | | |

| Variable | Subjects | | $\chi^2$ |
| | Treatment (n = 21) | Control (n = 349) | |
| --- | --- | --- | --- |
| Earn AA Degree | 43% | 50% | 1.136 |
| Earn AS Degree | 52% | 49% | |
| Earn Certificate | 5% | 2% | |
| No Degree Plan | 0% | 0% | |
| First Generation in College | | | |
| Yes | 38% | 32% | .264 |
| No | 62% | 67% | |
| Pell Qualifying | | | |
| Yes | 52% | 48% | .163 |
| No | 48% | 52% | |

Note: $p < .001$ for ***

Other missing data values included high school GPA. A data analyst tasked with providing data to the author stated the system used to upload transcripts into the database often does a poor job, which results in spotty data (personal communication, April 19, 2017). In the end, missing data represented approximately 50% of high school GPAs. Again, the number of missing values and variables that would be used to predict high school GPA precluded using a multiple imputation method or maximum expectation method. The literature review revealed high school GPA is traditionally an important predictor. Therefore, not using it presented the possibility of violating the no

unmeasured covariates central to PSM. Randomly, the treatment group possessed 18 of 21 high school GPAs and the control group was missing half. Therefore, an expectation maximization algorithm was run in SAS (Version 9.04) to fill in the three missing high school GPAs from all students who had GPA data ($n = 206$). However, for the control group, a different approach was used. The sample size needed to perform PSM was smaller than the available pool of subjects for one-to-one matching. However, the reduction in available control students could prevent one-to-many matching. PSM rests on having no unmeasured covariates. So, the author explored keeping the GPA students and removing the students lacking GPA. Hence, two new groups were created: a control group with high school GPA and one without. A test of homogeneity was conducted on the two groups to ensure that the two groups did not differ in a meaningful way. This would make removing the group without GPA data acceptable. The results from the analysis are summarized in Table 8. As can be seen, only two variables showed any significant difference ($p < .05$): the first-time in college (FTIC) and enrollment status.

Table 8

*Crosstabulations of Covariates and Control Subjects by High School GPA*

| Variables | Control Subjects | | $\chi^2$ |
|---|---|---|---|
| | With GPA (n=168) | Without GPA (n=179) | |
| Gender | | | |
| Male | 67 (-.91) | 80 (.91) | .82 |
| Female | 101 (.91) | 99 (-.91) | |
| Ethnicity | | | |
| Caucasian | 12 (-.04) | 13 (.04) | 4.05 |
| Hispanic | 68 (1.01) | 63 (-1.01) | |
| African American | 50 (-1.93) | 71 (1.93) | |
| Other | 38 (1.10) | 32 (-1.10) | |
| Enrollment Status | | | |
| Full-Time | 126 (3.43) | 103 (-3.43) | 11.77*** |
| Part-Time | 42 (-3.43) | 76 (3.43) | |
| First-Time in College (FTIC) | | | |
| Yes, First Time | 138 (11.24) | 39 (-11.24) | 126.33*** |
| No, Returning/Transfer | 30 (-11.24) | 140 (11.24) | |

| Variables | Control Subjects | | $\chi^2$ |
| --- | --- | --- | --- |
| | With GPA (n=168) | Without GPA (n=179) | |
| **Degree Plan** | | | |
| Earn AA Degree | 72 (-1.59) | 92 (1.59) | 3.87 |
| Earn AS Degree | 89 (1.33) | 82 (-1.33) | |
| Earn Certificate | 5 (1.23) | 2 (-1.23) | |
| No Degree Plan | 2 (-.38) | 3 (.38) | |
| **College Entrance Exam** | | | |
| Yes, Took Entrance Exam | 31 (1.44) | 23 (-1.44) | 2.07 |
| No Entrance Exam | 137 (-1.44) | 156 (1.44) | |
| **First Generation in College** | | | |
| Yes | 56 (.18) | 58 (-.18) | .03 |
| No | 112 (-.18) | 121 (.18) | |
| **Pell Qualifying** | | | |
| Yes | 84 (.78) | 82 (-.78) | .61 |
| No | 84 (-.78) | 97 (.78) | |

Note: *** = $p < .001$. Standardized residuals appear in parentheses below group frequencies.

In addition to the categorical variables, the age variable was analyzed for significant differences between the two groups. The Mann-Whitney test uncovered significant differences in the ages of those with a high school GPA (*Mdn* = 18) and those without (*Mdn* = 20), $z$ = -11.10, $p$ < .001. The significant differences in FTIC and age guided analysis toward seeing if these variables were related. Consequently, a Mann-Whitney test performed on age with the FTIC groups and Enrollment Status revealed differences existed between both the FTIC groups ($p$ < .001) and Enrollment Status groups. A $\chi^2$ test of independence also revealed that part-time enrolled students were between 1.4 and 2.7 times more likely to be returning students while full-time enrolled students were 30% more likely to be FTIC ($\chi^2(1)$ = 20.95, $p$ < .001). The conclusion is, those who are FTIC and enrolled full-time lean toward being younger and more likely to have high school GPAs than those with previous college and enrolled part-time, who lean toward being older. The treated students were younger, FTIC, and enrolled full-time. The older students who are inclined to have earned credits previously and have part-time schedules are less likely to be matched by propensity score. The author determined from the overall results of the analysis, removing those without high school GPAs to be able to match on that covariate would produce less bias than the larger sample without being able to use high school GPA.

In the end, 168 control students were available to match with the 21 treatment students. All students had complete data after the above analysis and used in the PS Matching function of SPSS Statistics (Version 24). In the end, the procedure used 12 variables from those provided by the institution. The variables are described in Table 9.

The benefit to other institutions lies in the fact that these data are regularly collected from all students. The analysis process to prepare the data utilizes simple statistical tests that can be performed in many software packages. Hence, resources and data needed to assess new programs are readily available using the methodology described in the dissertation.

Table 9

*Covariates Used to Calculate Propensity Score from Available Data*

| Variable | Level of Measurement | Description |
| --- | --- | --- |
| Treatment | Nominal | The student belongs to the first-year program. (0 = No, 1 = Yes) |
| Caucasian | Nominal | The student identified as Caucasian. (0 = No, 1 = Yes) |
| African-American | | The student identified as African-American. (0 = No, 1 = Yes) |
| Hispanic | | The student identified as Hispanic. (0 = No, 1 = Yes) |
| Gender | Nominal | The gender selected at admission to the college. (1 = Male, 0 = Female) |
| Age | Ratio | The age calculated from birthdate given the college. range = 18 to 56. |
| First Generation in College | Nominal | The student indicated that neither parent went to college at admission. (Yes=1, No=0) |

| Variable | Level of Measurement | Description |
|---|---|---|
| FTIC | Nominal | The student was not previously enrolled in higher education. (Yes=1, No=0) |
| Enrollment Status | Ordinal | Based on the number of credit hours taken in the Fall 2016 semester. (1 = Full-time, more than 11 hours; 0 = Part-time, less than 12 hours) |
| SES | Nominal | Pell Grant status was used as a proxy for socio-economic status. (0 = Not Pell Qualifying; 1 = Pell Qualifying) |
| Entrance Exam Taken | Nominal | The student took the SAT or ACT. (0 = No, 1 = Yes) |
| High School GPA | Continuous | Cumulative high school GPA as transcribed from records. range = 1.5 to 4.0 |

Note: the ethnicity variable is separated due to PS Matching handling only continuous and dichotomous variables.

## The PSM Analysis

Once the covariates are determined and the data are properly formatted, the PSM was ready to begin. What follows in this section is a discussion of which PS Matching options were run and ultimately which option was chosen for the analysis of differences. All the options ran through SPSS Statistics (Version 24) and its PS Matching algorithm. There exist other options in other statistical packages. However, when considering ease of use and diagnostics of the matching, SPSS was the recommended tool at the time of this writing.

A good reason to use SPSS Statistics (Version 24) rests on the diagnostic features available. The results give not only the propensity score values and the

matching treatment subject, but also the graphs produced assist in evaluation of the matches. Efforts to determine the appropriateness of the matches begins with the standard mean difference: how different the average scores of the two groups are. Ideally, the differences will equal zero. However, real data rarely result in zero. Consequently, Cohen's *d* allows the researcher to determine how different the means are. Again, the literature suggests that a $|d| > .25$ implies enough imbalance between the covariates to be a concern. SPSS Statistics (Version 24) provides this analysis as part of the output.

The discussion starts with the full matching results obtained from the data. Next, the nearest neighbor results were assessed for matching. Finally, the optimal matching results were evaluated for bias. The section concludes with the determination of the best option given the diagnostic results.

<div align="center">Full Matching</div>

The process for full matching in PS Matching involves assigning weights to every control unit to balance the propensity scores as seen in *Figure 6*. Using every member of the control group creates an advantage when using this option. Without reducing sample size, the ability to detect differences remains higher than the other methods where decreased sample size reduces a test's ability to detect meaningful differences. However, the increased power is balanced by reduced parsimony in analysis and the potential for one weight to dominate. To analyze the groups now requires multiplying variables by the weights and calculating averages. The increased steps increase time and possible errors. As for large weights, the output from SPSS Statistics (Version 24)

<div align="center">80</div>

shows three cases with weights of eight and six cases with weights of four. These nine

cases probably do not overwhelm the other cases, but they are contributing six times

more to the analysis than the 87 cases with *psweight* = .092.



*Figure 6.* Screenshot of PS Matching Using Full Matching Option. Psweight records the

weight of each case.

       Yet, while parsimony is preferred, the overall better analysis should be selected.

Therefore, the diagnostics were inspected to see if the data yielded more accurate

results from this method. The first diagnostic observed was the summary of unbalanced

covariates. Table 10 shows three covariates that are unbalanced, but the standard

mean difference is missing due to the method of matching. However, PS Matching

identified three covariates. This indicates a potential issue going forward.

Table 10

*Summary of Unbalanced Covariates (|d| > .25) for Full Matching*

| Subsamples | Covariates | Means Treated | Means Control | Std. Mean Diff. |
|---|---|---|---|---|
| (all cases) | TimeStatus1 | 1.000 | .977 | . |
| | FTIC1 | 1.000 | .984 | . |
| | FTAV1 | 1.000 | .993 | . |

Next, the distribution of propensity scores, in the form of a jitter plot, provides

information on how well the scores were matched. The matched control distribution

should look like the matched treated distribution. *Figure 7* shows a group of small

propensity scores that are small circles, followed by controls of varying size circles. This

is the weighting effect in a visual form. The treated propensity scores lie above .1;

therefore, the control students below that have very little weight so that their outcomes

contribute little to the overall analysis. Between .1 and .15 there is a group of matched

treated and matched control. The overlap demonstrates common support, similar

scores for both groups. However, the weighting makes it difficult to determine the level

of common support. More concerning, the matched treated area between .25 and .35

contains four students. Yet, the matched control holds 14 with weighting larger than
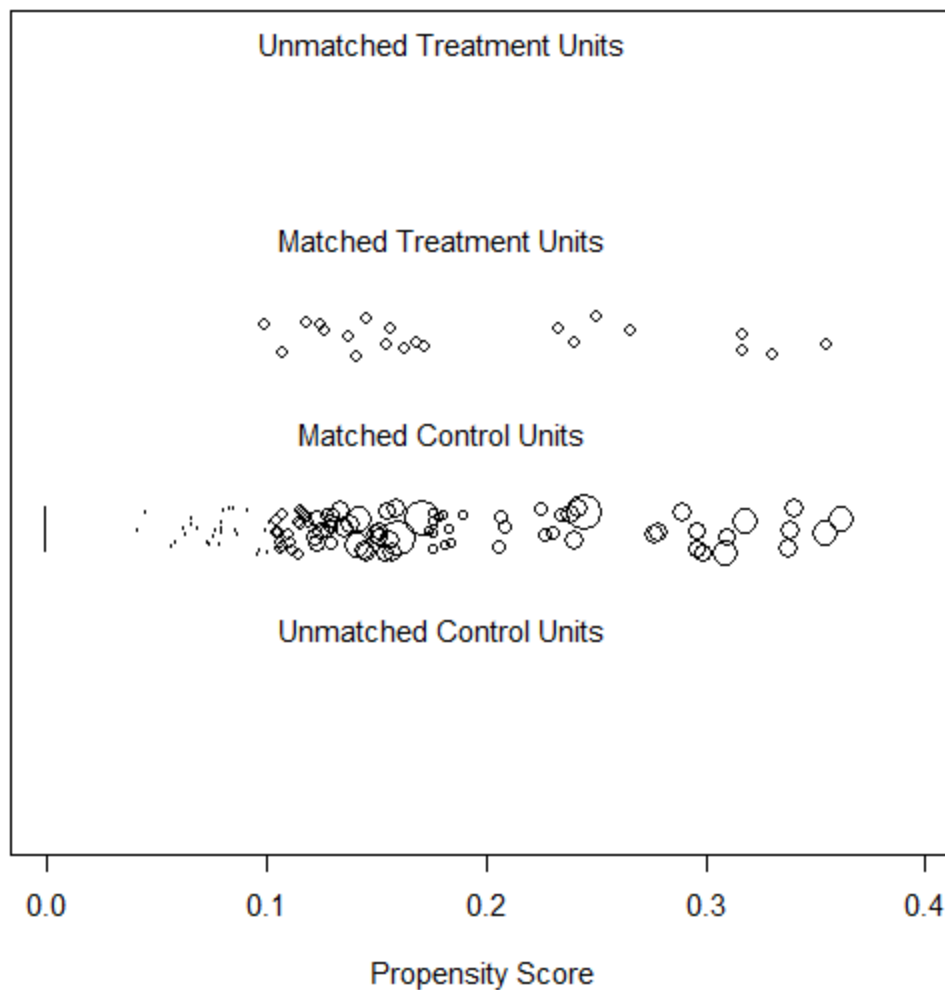
one.

*Figure 7.* Jitter Plot of Propensity Scores Produced by the Full Matching Method.

Third, side-by-side histograms provided insight into the common support of the propensity scores. The closer the shapes matched between the treated and control, the more likely good matches would result and eliminate bias. PS Matching constructs four histograms: two showing common support before matching and two showing common support after matching. However, the full matching method results in no change between before and after matching. This is due to the scores being adjusted by weight and not by removing bad matches.

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Finally, PS Matching creates histograms of the standardized differences of the covariates. The matching algorithm should reduce the differences indicating that bias was reduced due to the algorithm. *Figure 8* shows that, in fact, the differences have been reduced considerably.
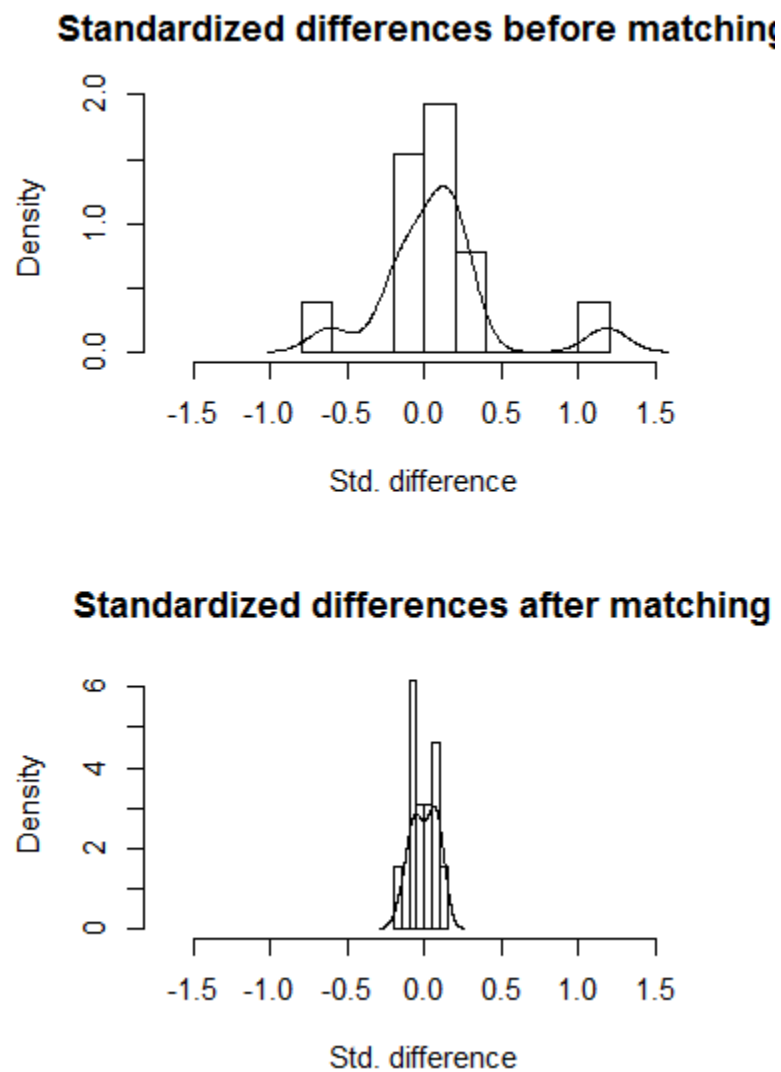
**Standardized differences before matching**



**Standardized differences after matching**



*Figure 8.* Standardized Differences Before and After Matching.

The choice of method ultimately rests on how correctly it interprets the data and parsimony. It should be as simple as possible and no simpler. The full matching method demonstrated issues with three covariates and the jitter plot. Additionally, it is more difficult to analyze data due to weighting the variables. Nevertheless, the method reduced standardized differences drastically and retained the largest sample size. All these things were considered before the final choice was made.

<center>Nearest Neighbor</center>

The next option selected was the nearest neighbor algorithm. From the literature, appropriate matches use a caliper of .25 Mahalanobis distance to ensure that good matches are obtained (Ripley, 2015; personal communication, June 2017). The Mahalanobis distance is appropriate due to the nature of the covariates being treated as vectors, and the Mahalanobis distance is a vector measurement. Matches farther than .25 away tend to be less like the treatment subject overall; therefore, the algorithm rejects those controls for matching. The SPSS Statistics (Version 24) routine ran the data provided by the institution. The diagnostics were then evaluated to determine if this method represented the data better than the other methods.

The first diagnostic provided by SPSS Statistics (Version 24) was the summary of unbalanced covariates. For the first-year program, it is summarized in Table 11. The table shows that the nearest neighbor algorithm produced five out of 12 covariates with significant differences between the treatment and control subjects. While research into PSM finds nearest neighbor matching without replacement and using a caliper typically

does an adequate job of matching, for these data the diagnostics reveal the matches are not optimal.

Table 11

*Summary of Unbalanced Covariates (|d| > .25) for Nearest Neighbor Option*

| Subsamples | Covariates | *Means Treated* | *Means Control* | *SD Control* | *Std. Mean Diff.* |
|---|---|---|---|---|---|
| (all cases) | Hispanic | .333 | .571 | .507 | -.493 |
| | Caucasian | .286 | .143 | .359 | .309 |
| | Male | .667 | .810 | .402 | -.296 |
| | Female | .333 | .190 | .402 | .296 |
| | Pell | .524 | .667 | .483 | -.279 |

Additional diagnostics include viewing the jitter plot of the propensity scores. As matches are made based on these scores, observing the distribution makes sense. SPSS Statistics (Version 24) creates an excellent jitter plot for determining the quality of the matching from the method. The matches from the first-year program are illustrated in *Figure 9*. Looking at the figure, focus on the matched treatment and control units. Notice that while the values are in about the same range, the distributions mirror one another moderately. It demonstrates that there is common support and that matches are close based on propensity score, because the caliper ensures closely paired data.
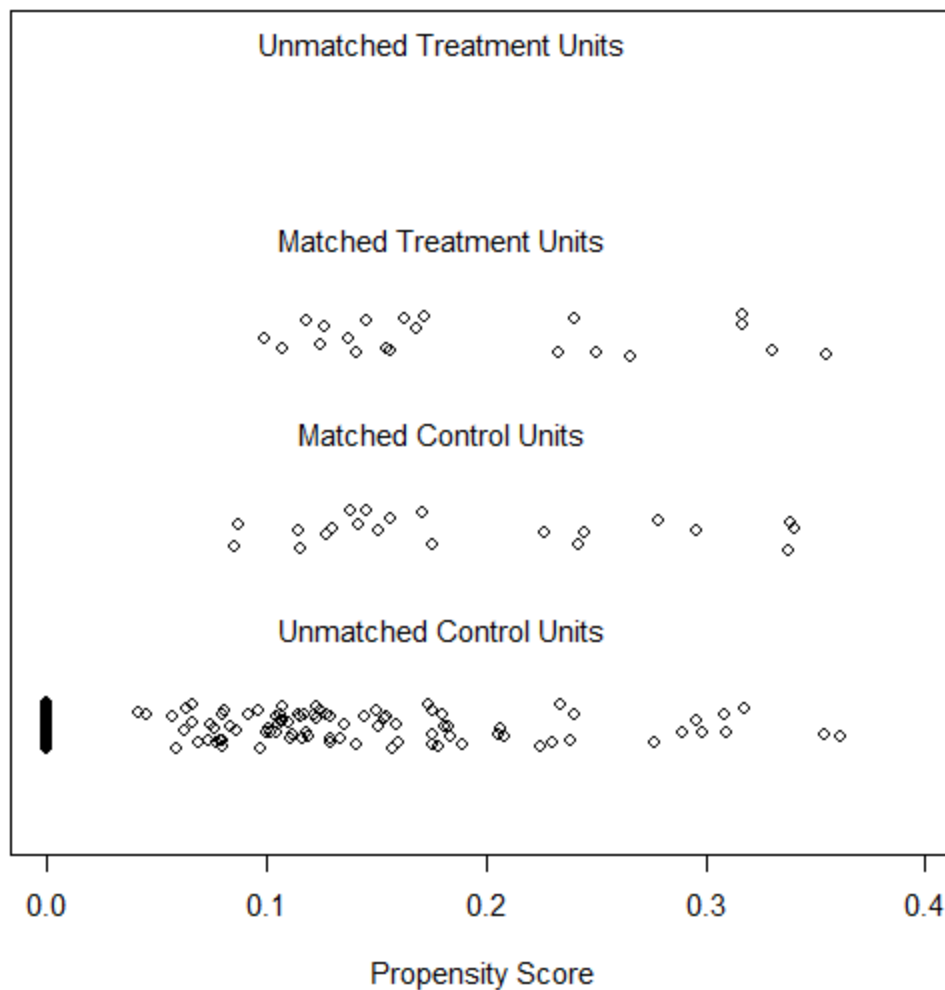
*Figure 9.* Distribution of Propensity Scores from the Nearest Neighbor Matching

Algorithm.

Additionally, the histogram of the propensity scores for the matched treatment

and control units contribute to the evaluation. In SPSS Statistics (Version 24), the

unmatched and matched histograms for the two groups are provided. This allows the

researcher to see if differences existed before matching and if those differences

disappear after matching. The histograms for the first-year program are displayed in

*Figure 10*. Looking at the far left, notice the difference in the shape of the treated and control graphs. This indicates that matching is needed to avoid confounding. Looking at the right graphs, notice that the shapes match better for the matched groups but differences still exist. However, the differences were minor and showed very good common support.
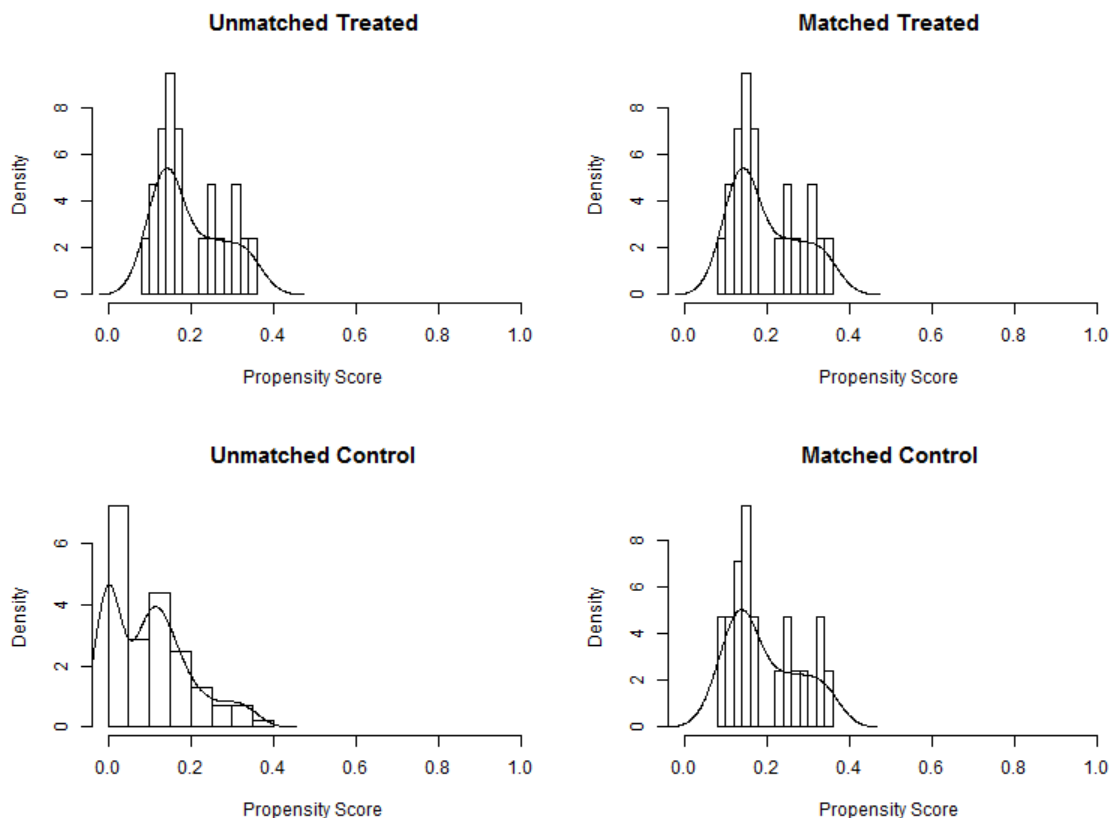


*Figure 10*. Histograms Comparing Matched and Unmatched between Treated and Untreated Using Nearest Neighbor.

Lastly, the standardized differences between the covariates before and after matching are examined. The smaller the differences, the more balanced the covariates

are between the treated and control students. *Figure 11* illustrates the effect of the

nearest neighbor procedure on the differences.

**Standardized differences before matching**



**Standardized differences after matching**



*Figure 11*. Histograms of Differences Between Covariates Before and After

Matching Using the Nearest Neighbor Method.

The differences before matching spread beyond one standard deviation. This

would suggest that matching is needed to reduce bias. The differences after matching

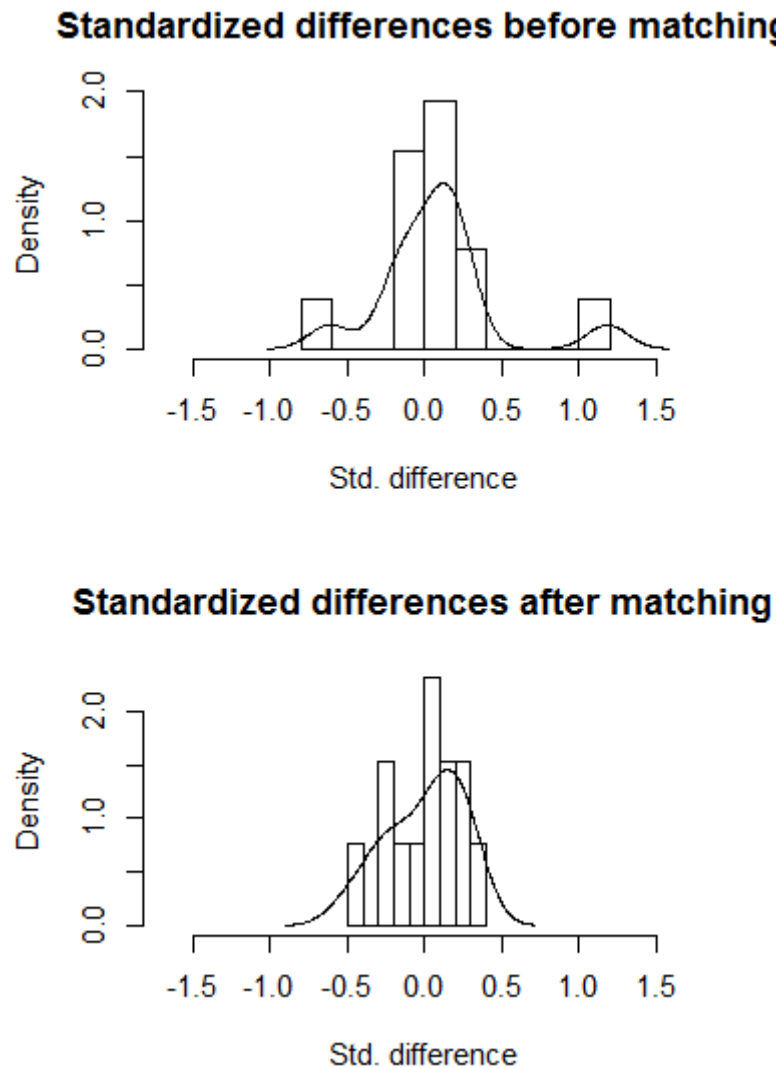reduce spread to half a standard deviation or less. Worth noting is that both tails are almost half a standard deviation wide. This will be important when discussing differences between the near neighbor results and the optimal matching results.

## Optimal Matching

Finally, the author used the optimal matching method to derive appropriate pairs from the treated and control subjects. Again, the diagnostics produced were analyzed to determine the fit of the matches. Here we see that the summary of unbalanced covariates is more favorable with this method. Only two covariates, age and first-generation in college, exceed the recommended Cohen's *d* of .25. The results of the mean difference and standard deviation for the two covariates are presented in Table 12.

Table 12

*Unbalanced Covariates (|d| > .25) Produced by Optimal Matching*

| Subsamples | Covariates | Means Treated | Means Control | SD Control | Std. Mean Diff. |
|---|---|---|---|---|---|
| (all cases) | Age | 18.286 | 18.048 | .218 | .425 |
| | First-Generation | .381 | .238 | .436 | .287 |

Again, the author returned to the jitter plot of the propensity scores to determine how well the matching method performed. *Figure 12* shows the matching from the first-year program data. Of note, there are no dots indicating unmatched treatment units at

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the top of the figure. The middle two plots show similar matching to the nearest neighbor plot in *Figure 9*. The plots of the matched pairs align very well, showing common support and good matching. Looking at the Matched Treatment Units plot, one can detect three distinct groupings. Those groupings appear in the Matched Control Units plot also. Finally, the unmatched scores in the bottom plot demonstrate why matching was needed before analysis, many control student were different based on measured covariates.
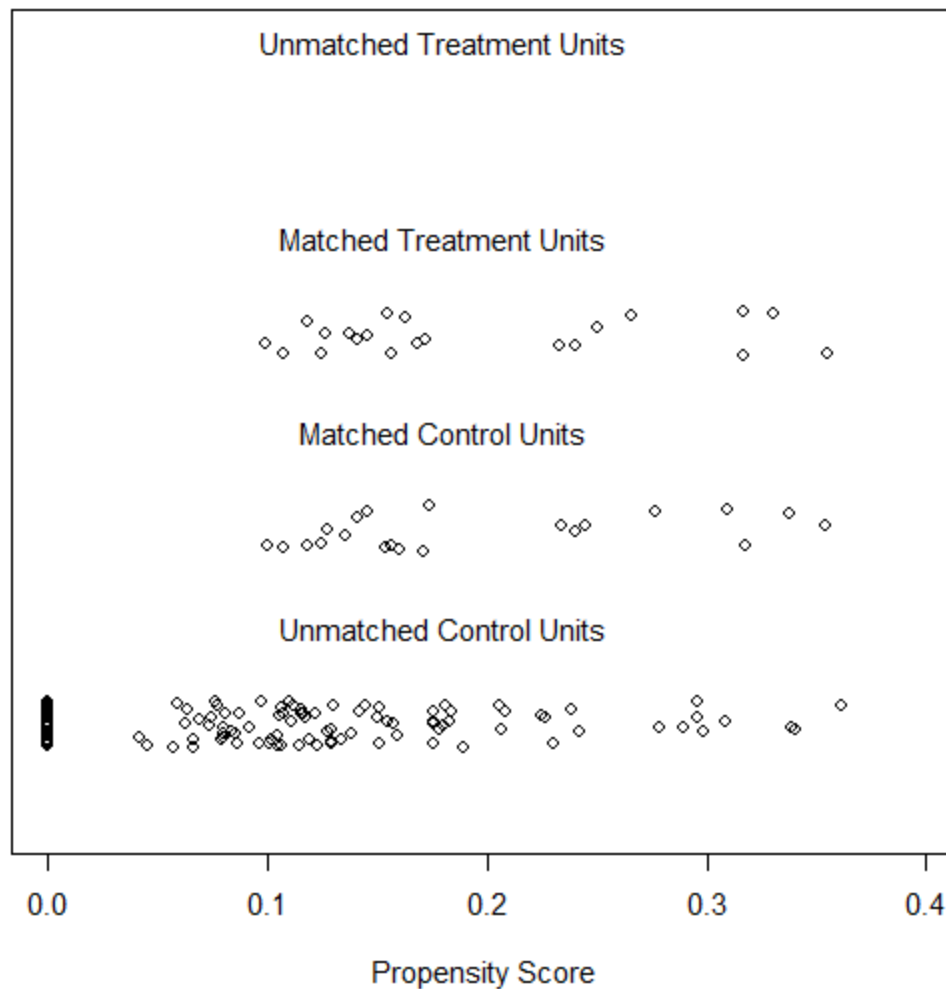


*Figure 12*. Jitter Plot of Propensity Scores Produced by the Optimal Matching Method.

Next, the histograms of the propensity scores were analyzed. *Figure 13* shows how well the optimal matching performed. While the histograms displayed in *Figure 10* were close matches, the histograms of matched treated and control in *Figure 13* are identical. Again, the optimal match displayed superior diagnostics to the alternative methods for these data.
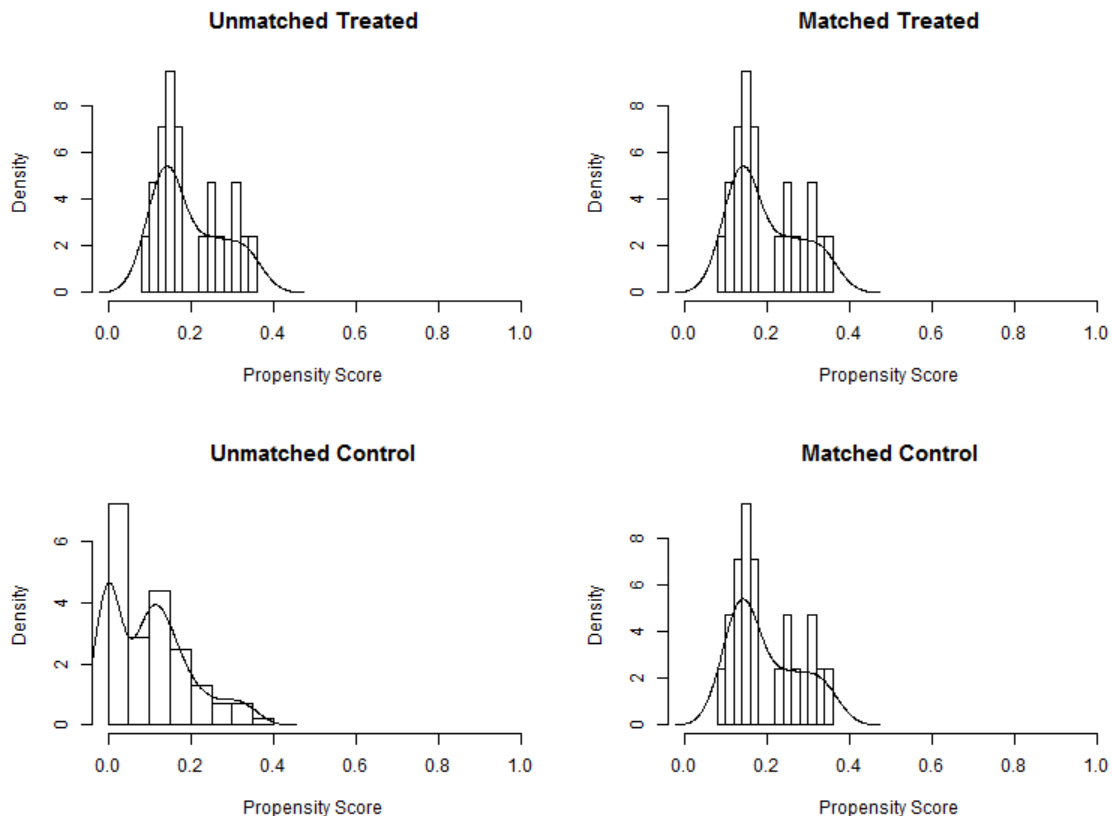


*Figure 13.* Histograms Comparing Matched and Unmatched between Treated and Untreated Using Optimal Matching.

Finally, *Figure 14* provides a histogram of the standardized differences between the covariates. The larger the difference, the more potential bias present in the analysis. Before the matching, the histogram reveals that differences exceed one standard

deviation. After matching, the differences shrink to less than half a standard deviation. Observe, the left tail appears to be less than 0.25 standard differences. The full matching performed better for this test as both tails remained below 0.25 standard differences. The worst performing of the three was the nearest neighbor algorithm with both tails being about .5 standard differences.





*Figure 14*. Histograms of Differences between Covariates Before and After Matching Using the Optimal Method.

Choice of Method

The above analysis guided the author to choose the optimal matching method for these data. First, it has fewer unbalanced covariates at two. The other methods generated three for t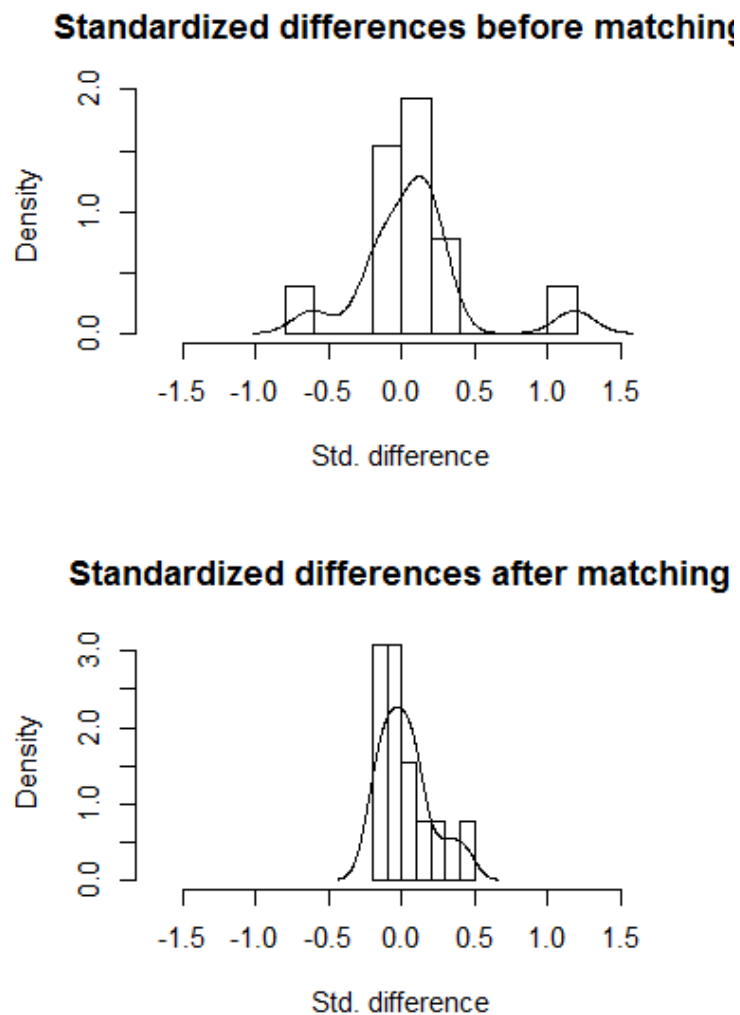he nearest neighbor and five for the full matching. Second, the histograms of the propensity scores for the matched treated and matched controls corresponded better for optimal matching than the nearest neighbor and full matching algorithms. Third, the standardized differences were similar for one tail of the optimal and the full matching; while one tail was a little worse but still within an acceptable range. The nearest neighbor method performed the worst in this diagnostic. Finally, optimal matching proves simpler to implement than full matching while also performing better in all but one diagnostic. Consequently, all the analysis of the pairs will be done using the students selected by the optimal matching method.

Analysis of the Matched Pairs

While there is some discussion within the literature about the appropriate tests to utilize with matched data, for this dissertation paired tests were used. From the previous section, it was shown that the pairs appeared well matched. Conceptually, this implies that the same participant took the treatment and was in the control group. Therefore, the variance in data depends upon the individual, and to detect differences this needs to be accounted for in the chosen test.

Overall, the first-year program showed no statistically significant results for any of the research questions. Yet, the differences yielded positive effects for all the questions. The pilot year of the study made a small favorable contribution to student success when

compared to the control students. While this is a positive result, it is a point estimate and further research will be needed to prove the positive effect is real or simply an isolated result. The results are discussed in the following sections organized by the individual research questions.

## Findings for Research Question 1

To determine if there exists a significant difference between the persistence rates of the cohort and the matched group, a $\chi^2$ test of independence was used. Evaluation of the groups was done in SAS (Version 9.04) using the PROC FREQ command with the CHISQ and CMH options. The CMH option provides information on the odds ratio to determine the effect of the first-year program on persistence. Table 13 presents the persistence rates for both fall and spring semesters.

Table 13

*Differences in Persistence of the Cohort and Control Students in the Fall and Spring Semesters*

| Persistence | Cohort | | Control | | $\chi^2$ | *P* | *OD* |
|---|---|---|---|---|---|---|---|
| | Yes | No | Yes | No | | | |
| Fall to Spring | 15 | 6 | 16 | 5 | .123 | .726 | 1.28 |
| Spring to Summer | 14 | 7 | 15 | 6 | .111 | .739 | 1.25 |

Note: *OD* = odds ratio

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While the effect was not statistically significant, it was positive. The odds ratio shows that students exposed to the first-year program were 28% more likely to re-enroll in spring with a 90% confidence interval varying from 60% less likely to persist to 4.1 times more likely to persist. Additionally, students exposed to the first-year program were 25% more likely to re-enroll in summer with a 90% confidence interval varying from 51% less likely to persist to 3.8 times more likely to persist. The power of the test due to sample size was limited to 10%; therefore, a significant result may exist and was simply not detected. Additionally, this analysis includes all students who started the first-year program, regardless of their retention in the program. The multiple linear regression includes number of semesters retained to determine the cumulative treatment effect with the outcomes in Table 16.

These results point to one of two possibilities for the program. One possibility is that the program asks the students to do too much. Students become overwhelmed and leave college. The negative persistence rates in the confidence interval point to this possibility. The other possibility is that the extra support works well to assist students in being successful. The student connects with peers, faculty, and the institution in a meaningful way and persist toward degree even when obstacles are encountered. The positive persistence rates in the confidence interval point to this possibility. Again, more data from other multiple-intervention programs is needed to determine which possibility is correct.

Findings for Research Question 2

To determine if there exists significant differences in GPA between the cohort and the matched group, paired t tests were used. The evaluation between the two groups was done in SAS (Version 9.04) using the PROC TTEST command. Table 14 presents the results for the differences in GPA for both the fall and spring semester.

While the fall semester differences in pairs were not statistically significant, the moderate effect size is very encouraging for the pilot. Again, the power of the test due to the sample size was 10%. Consequently, it would have been difficult to find statistical significance. Finally, the mean difference was .23 points higher in GPA with a 90% confidence interval varying from .38 points below to .84 points higher for the first-year students over the matched students. The spring semester showed a weak effect size with cohort students earning .17 points more in GPA than the matched students. The 90% confidence interval varies from .41 points less to .76 points higher for the first-year program students.

Table 14

*Differences in the GPAs of the Cohort and Control Students in the Fall 2016 and Spring*

*2017 Semesters*

| GPA | Cohort | | Control | | $t(20)$ | $p$ | Cohen's $d$ |
|---|---|---|---|---|---|---|---|
| | $M$ | $SD$ | $M$ | $SD$ | | | |
| Fall | 2.28 | 1.44 | 2.05 | 1.46 | .66[a] | .520 | .51 |
| Spring | 2.13 | 1.48 | 1.96 | 1.38 | .51 | .615 | .12 |

[a]the Wilcox ranked sign test had a notably different result of $S = 29.5$ and $p = .281$ No other differences were notable in the analysis.

## Findings for Research Question 3

To determine if there exists a significant difference between the credits earned in the cohort and the matched group, paired t-tests were used. The evaluation between the two groups was done in SAS (Version 9.04) using the PROC TTEST command. Table 15 presents the outcome of the tests. Again, the results are not statistically significant but there is a weak positive effect from being involved in the first-year program. Also, due to the power of the test being 10% it would have been difficult to detect a significant difference. Furthermore, the analysis focuses on those who started in the program and does not separate results for each semester. The mean difference between the pairs was .86 credits more earned on average, while the 90% confidence interval shows the cohort students earning between 1.4 credits less and 3.1 credits more than the control students in the fall. The difference increases in the spring semester to 1.4 credits more on average than the control student. Hence, a cumulative

effect may exist each semester as the difference grows. Finally, the 90% confidence interval for the cohort students falls between 2.7 credits less and 5.5 credits more than the matched students in the spring.

Table 15

*Differences in the Credits Earned between the Cohort and Control Students in the Fall and Spring Semesters*

| Credits Earned | Cohort | | Control | | t(20) | P | Cohen's d |
| --- | --- | --- | --- | --- | --- | --- | --- |
| | M | SD | M | SD | | | |
| Fall | 8.71 | 4.92 | 7.86 | 5.15 | .65 | .521 | .17 |
| Spring | 15.71 | 10.21 | 14.33 | 10.35 | .58 | .569 | .13 |

Findings for the Exploratory Question

To determine the measured impact of the program on student persistence, a multiple linear regression model was built using only students with high school GPAs (N = 189). The $R^2$ values and standardized β weights produced by the model are summarized in Table 16.

The model was constructed and evaluated with the PROC REG function in SAS (Version 9.04) with the STB statement for complete evaluation. The results of the model reveal that most of the covariates do not contribute significantly to the prediction. However, treatment resides in the third most significant spot. With a *β* = .11, it shows a weak but positive effect on credits earned. This result indicates students who are

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retained longer in the first-year program tend to earn more credits. Again, this small but positive finding is encouraging for a pilot program. Finally, note that high school GPA was the most significant predictor of credits earned. This supports removing all the students without high school GPA to ensure all important covariates could be included in calculating propensity scores.

Table 16

*Summary of Multiple Linear Regression Analysis Predicting Credits in Spring with Treatment Variable*

| Variable | B | SE B | t | p | B |
|---|---|---|---|---|---|
| Pell | -0.01 | 1.38 | -0.01 | 0.995 | -0.000 |
| First_Gen | -0.82 | 1.31 | -0.63 | 0.532 | -0.044 |
| CollegeEntrance | 2.99 | 1.53 | 1.96 | 0.052 | 0.134 |
| GoalAS | -0.08 | 2.81 | -0.03 | 0.978 | -0.004 |
| GoalAA | -0.96 | 2.90 | -0.33 | 0.741 | -0.051 |
| FTIC | -2.60 | 1.73 | -1.51 | 0.134 | -0.107 |
| HS_GPA | 7.70 | 1.45 | 5.32 | <.001 | 0.386 |
| Age | 0.46 | 0.37 | 1.24 | 0.217 | 0.093 |
| Caucasian | 3.80 | 2.45 | 1.55 | 0.123 | 0.205 |
| Hispanic | 2.39 | 2.48 | 0.97 | 0.335 | 0.129 |
| AfricanAmer | 0.31 | 2.64 | 0.12 | 0.906 | 0.015 |
| Gender | -1.06 | 1.26 | -0.84 | 0.400 | -0.059 |
| Treatment | 1.03 | 0.63 | 1.64 | 0.104 | 0.111 |

Note: $R^2$ = .25 ($N$ = 189, $p$ < .001)

# CHAPTER FIVE: CONCLUSION

This chapter summarizes the results of the study by research question. First, the author discusses how well the goal of the program was met. Then, limitations of the study in context. Finally, the recommendations section provides guidance for future research.

In brief, the first-year program produced a small positive improvement in student achievement when controlling for student characteristics. This result supports the theory of multiple interventions being worth investigation to improve overall graduation rates among all students. Students who participated in the first-year program showed weak positive increases in persistence from semester to semester, GPA, and credits earned. Also, the analysis demonstrated that for every semester retained in the first-year program, there was almost a 9% increase in the number of credits earned (1-1.5 more credits) over similar students. This is similar to the results recorded by Johnson and Romanoff (1999). In their study, no statistical significant results were found in the first year either. However, the students did report greater commitment to the degree program. This commitment may translate into greater persistence, which was seen by students who stayed in the program longer.

## Research Questions

### Research Question 1

To what extent does the persistence rate of students who participated in the program differ from a matched comparison group of students who do not participate? The students who participated in the program did not do significantly better, with

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approximately 28% better persistence in fall and 25% better persistence in spring over the matched group. These results show promise in the multiple intervention approach with community college students. These results demonstrate the gap in graduation at the institution could be closed if the program evolves from lessons learned and is brought to scale as planned by the administration. Persistence represents the first step in achievement because it indicates that students are having at least some success and maintaining motivation for a degree goal. These results are also consistent with the literature reviewed for each of the individual interventions when persistence was measured.

<div align="center">Research Question 2</div>

To what extent does the GPA of students who participated in the program differ from a matched comparison group of students who do not participate? Students who started in the first-year program earned on average a 19% higher GPA than the matched students in the fall. This difference dropped to about 5% in the spring. This decrease might be explained because the author used the same GPA from fall to spring of students who did not persist. The initial analysis focused on students who started in the program and their results over the course of the year. In other words, the analysis was based on intent to treat. Nevertheless, secondary analysis of only students who persisted from either group produced little change in the effect. Again, this result was not significantly different from the control students, but the positive result is encouraging for a small pilot. Research shows that success in the first year of a student's academic career dramatically increases his or her likelihood of earning a degree. This result also

supports the theory of multiple interventions for community college students improving persistence and increasing graduation rates.

## Research Question 3

To what extent do the credits earned of students who participated in the program differ from a matched comparison group of students who do not participate? The first-year program increased the number of credits earned by students who started the program by almost 7% over the matched students in the fall. Again, the data showed a smaller effect in the spring as the difference fell to about 5%. Furthermore, the findings remain statistically insignificant. This outcome supports the theory of multiple interventions and encourages further research into the effectiveness for a multitude of students. Additionally, the research should be rigorously conducted to ensure the true efficacy of the theory is resolved.

## The Exploratory Question

What was the measured impact of the program on student achievement? This question required the insight of length of treatment and not simply intent to treat. The number of semesters retained provided a measure of overall effectiveness for the program. The credits earned assessed overall student achievement. Students must enroll in the next semester and be successful in those classes to continue to accumulate credits. Hence, it provides a good measure of accomplishment to determine how the program affects students. The regression analysis showed that the program was the third most important variable when predicting credits earned after high school GPA and having taken a college entrance exam. As with the previous research

questions, there was no significant difference, but a small positive impact was detected. However, the data included all students who had a high school GPA, not simply the matched group. Consequently, students retained in the program earned on average 9% more credits by the end of Spring than students in the control group. Again, this lends credibility to the theory of multiple interventions helping students attain more success than they would otherwise. While academic preparedness continues to be an important predictor, those coming to institutions less prepared can profit from the advanced support offered by a program like the one in this study.

## Limitations

The sample size represents the most serious limitation. The sample size influences the ability to detect differences between the groups. The power of each test was calculated to be approximately 10% for the sample size and differences observed. Consequently, even though positive effects were shown, none of the effects was pronounced enough to be significantly more than expected by natural variation. The fact that five students from the program were not in the provided data exacerbated the issue. Furthermore, missing students leave uncertainty about whether the effect size is overstated or understated.

The number of students with high school GPA data in the provided dataset altered the types of PSM analysis that could be done. Initially, the author planned to do 1:1 and 1:5 matching to show other options available in SPSS Statistics (Version 24) and improve statistical power. Yet, the lack of high school GPA prevented utilizing options other than the 1:1. Thus, the power to detect differences from the multiple

matching schemes was unavailable. Potentially, the 1:5 choice enhances the detection of differences while reducing bias for the PSM algorithm. The author showed that more recent graduates had high school GPA data. So, over time this limitation should be resolved.

This dissertation was not a program evaluation. The purpose of this dissertation was two-fold. First, establish that the theory of multiple interventions can improve student success among community college students. Second, demonstrate the use and effectiveness of PSM in an educational study. Other institutions can follow the template provided and use available data to rigorously evaluate programs. However, the author's major focus was quantitative analysis and this leaves out the important qualitative data that give context to new programs. Hence, qualitative data collected at the institution were not used. Interview and survey data provide valuable insight into the fidelity of program execution and improve understanding about student choices. Consequently, no claim regarding the level of implementation of the program's interventions nor why students left the program is made.

Finally, this program was a pilot. The institution expended a great deal of effort to create and run the program for this first group of students. Furthermore, while the faculty were trained in the summer, no one knew what to expect from the first full year of the program. The author believes many lessons were learned that will improve the program in the coming years. Therefore, this makes the small positive improvement worth noting and the possibility that the results become more significant exists.

<p style="text-align: center;">Recommendations</p>

Because sample size was the defining limitation, the author recommends a larger sample size in the future. The institution plans to run four cohorts in the 2017-2018 academic year. This provides a substantial increase in the ability to detect differences between groups from 10% to between 25% to 50%. With four times the participants and the new understanding of the data provided by the institution, future analysis will contribute to the validity of the theory of multiple interventions. Other institutions wishing to implement this program should also start small and learn lessons, then add to their successes.

Also, evaluating complex new programs requires specialized software. While SPSS Statistics (Version 24) performed the PSM for the dissertation, other software packages continue to add features and simplify processes. Therefore, it is recommended that researchers and institutions continually update their understanding of advances in software and build their capacity to use them. Additionally, new methods are developed that improve understanding of the data and the world at large. PSM represents such a technique. Educators now possess the ability to make causal comparative inferences from observational studies. However, the fact that the technique was developed in 1984 and is seeing wide use in education only now indicates this is an area for improvement.

Furthermore, to appropriately evaluate the first-year program requires qualitative data in addition to the quantitative data. Focus groups, site visits, and surveys paint a rich picture of implementation, attitudes about the program, and reasons students

persist or depart. These data work in concert with persistence rates, credits earned, and GPA to deepen the researchers understanding of why things happened, not simply what happened.

The next recommendation involves investigating the admission process. High school GPA and taking a college entrance exam were the best predictors of credits earned in a semester. Moreover, analysis of the first-year program students revealed that no student with below a 2.5 GPA was retained in the program. Therefore, some students pose more risk of departing than others. Institutions must decide how best to partner with these students so that they can be successful. This can be done in two ways. First, create a cutoff for those students not likely to persist and provide a remediation program that will prepare them for college-level work. The institution runs such a program on a different campus that was the basis for the first-year program. Other institutions might follow the same path. Second, provide additional support immediately for those identified as at-risk. This additional support can take on many forms.

For instance, literature suggests one type of support would be the integration of advising with student learning support. Proactive advising is more effective when the solutions include academic support (CCCSE, 2012). Academic support includes writing centers, discipline-specific help using peer tutors, workshops on doing research, and a host of other services. Including academic support into the early alert and intervention protocols so that students receive just-in-time support for specific difficulties should lead to improve student achievement. Astin's (1984) and Tinto's (1975) theories hypothesize

that connecting the student to the institution in this way is a mechanism for persisting until graduation. Therefore, adding another layer of intervention should continue to provide meaningful results.

**APPENDIX: UCF IRB APPROVAL**

## NOT HUMAN RESEARCH DETERMINATION

From : **UCF Institutional Review Board #1**
**FWA00000351, IRB00001138**

To : **Joshua M Guillemette**:

Date : **April 19, 2017**

Dear Researcher:

On 04/19/2017 the IRB determined that the following proposed activity is not human research as defined by DHHS regulations at 45 CFR 46 or FDA regulations at 21 CFR 50/56:

| | |
|---|---|
| Type of Review: | Not Human Research Determination |
| Project Title: | The first-year program: can we improve student achievement through connection |
| Investigator: | Joshua M Guillemette |
| IRB ID: | SBE-17-12954 |
| Funding Agency: | |
| Grant Title: | |
| Research ID: | N/A |

University of Central Florida IRB review and approval is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are to be made and there are questions about whether these activities are research involving human subjects, please contact the IRB office to discuss the proposed changes.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

*Renea Carver*

Signature applied by Renea C Carver on 04/19/2017 08:49:18 AM EDT

IRB Coordinator

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