INTENTIONAL STUDENT-FACULTY INTERACTIONS: EVALUATING THE EFFECTIVENESS OF A COMMUNITY COLLEGE PROGRAM TO IMPROVE STUDENT RETENTION

by

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ABSTRACT

A program at Oakton Community College, the Persistence Project, creates intentional student-faculty interactions during the critical first six weeks of college and has demonstrated increased student within-year and year-to-year retention since its inception in spring 2016. Faculty Project participants commit to holding 15-minute meetings with each student in a Persistence Project class, learning students' names as soon as possible, engaging students in a get-to-know-you peer activity, administering an early student assessment, and providing constructive feedback. This dissertation is a quasi-experimental study of observational data from two Oakton cohorts of first-time in-college, traditional-aged students. The study determined if participation in a Persistence Project class influences retention when using propensity score analysis to control for student characteristics that are linked to student retention. The study, framed in Astin's input-environment-outcome impact model, included 28 covariates and 1,142 students in the fall 2018 cohort and 1,174 in the fall 2019 cohort.

This first statistical analysis of the Persistence Project did not demonstrate that the Project had a statistically significant influence on within-year or year-to-year retention of first-time in-college, traditional-aged students at Oakton Community College after using propensity score matching.

This study adds to the literature of how student-faculty interactions at community colleges influence student retention. It also provides a foundation for additional statistical studies of the Persistence Project that can continue to evaluate the treatment effects of the Project on student outcomes.

KEY WORDS: Persistence Project, propensity score analysis, retention, student-faculty interactions

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INTRODUCTION

Community colleges provide access to learning for students throughout their lives. This access provides a direct path to a career or indirectly via transfer to a four-year institution of higher education for an increasingly diverse student population (Bailey & Alfonso, 2005; Harper & Quaye, 2014). Community colleges' focus on access has shifted to include student success as their communities, legislators and policymakers, students, and students' families pressure them to improve student success outcomes, including retention, persistence, and completion. These outcomes have become synonymous with the quality of a college education. As community colleges implement initiatives to improve student outcomes, initiatives must include activities that intentionally increase student-faculty interactions in and out of the classroom. Initiatives that increase intentional student-faculty interactions are low-cost, faculty-driven strategies to improve student retention. Looking at an intentional student-faculty engagement model is warranted.

THE COMMUNITY COLLEGE CHALLENGE: LESS THAN DESIRED STUDENT SUCCESS OUTCOMES

Student success outcomes and academic quality are becoming increasingly important to state and federal governments that fund different aspects of higher education and to regional and disciplinary accrediting organizations. This is evident in the resurgence of states implementing performance-based funding (PF 2.0) or outcomes-based funding (OBF). OBF renews the call for higher education accountability and efficiency by focusing on retention, persistence, success, and completion. The importance of student success outcomes to external stakeholders is also evident in the shift of accrediting organizations' standards and criteria to include student learning and success outcomes (Biswas, 2006; Higher Learning Commission, 2019). Accrediting organizations have defined student outcomes and the associated accreditation standards. These standards require institutions to address student outcomes at course, program, and institutional levels.

As the costs of higher education and student debt increase, completion rates have remained relatively stagnant, supply-demand gaps have increased, and the value of a college credential has come under scrutiny (D'Amico et al., 2014; Holly & Fulton, 2017). The increasing cost of higher education and poor student outcomes also contribute to the stigma of a community college education. The stigma that community college education is of lesser quality than that of an education at a four-year institution, is attributed to a number of misperceptions. Parents, students, and community members may not understand the mission of community colleges and believe that community colleges are for students who need remedial work; or for students who could not get into a four-year college or university; or for students who want to get an "easy" career certificate (Gauthier, 2020). Therefore, a community college education is considered less rigorous and is undervalued. Poor completion rates perpetuate the stigma.

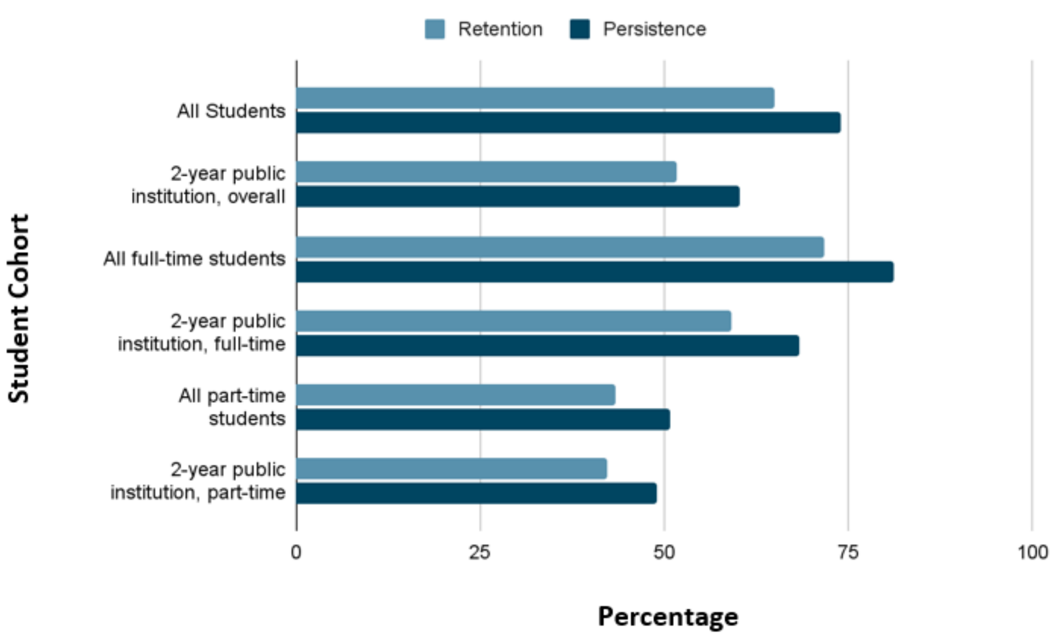
Despite an increased focus on improving student success outcomes of community college students, retention, persistence, and completion rates remain low but are improving slightly. Recent data from the National Student Clearinghouse Research Center (NSCRC) did indicate that six-year completion rates for the Fall 2012 cohort of students at two-year public institutions of higher education improved by 1.7% points (Shapiro et al., 2018). Increases in six-year completion rates were evident across all age, gender, and racial/ethnic groups, yet gaps still remain for Black and Hispanic students (Shapiro et al., 2018).

Even with the national focus on student success, and the considerable financial investment in improving student success outcomes, the increases are not significant. Retention, persistence and completion rates at community colleges are still low. When looking at six-year outcomes of those college students who enrolled in a two-year public institution in the fall of 2012:

- 27% earned a certificate or degree within six years of enrolling
- 14.5% were still enrolled at their institution
- 11.5% completed at another institution of higher education
- 46.1% stopped attending and did not enroll at another institution. (Shapiro et al., 2018)

Completion rates are likely to remain stagnant. This is evident in the indicators of student success, such as a first-year persistence and retention rates of the Fall 2009-2018 cohorts of all students enrolled in institutions of higher education. The NSCRC defines retention as the continued enrollment at the same institution of higher education in the fall term of students' first and second academic years. Persistence is defined as the continued enrollment at any institution of higher education in their first and second fall terms, which may be different from the institution students initially enrolled in (NSCRC, 2020). Since 2009 there has been very little variation in first-year student persistence and retention rates, and any improvements have been minor (NSCRC, 2020). It is evident that first-time, full-time students stay at the institution they originally enrolled in and return the next year at significantly higher rates than part-time students (Figure 1). It is also notable that students at two-year public institutions do not stay at the institution they originally enrolled in or persist at the same rates as all students, which includes public and private four-year institutions of higher education (see Figure 1). Retention and persistence rates, indicators of completion, are likely to remain stagnant and any incremental improvements will be minor unless student success initiatives are implemented more broadly and at the classroom level.

Figure 1. Average Retention of Persistence Rates for the National Fall 2009-2018 College Cohorts (NSCRC, 2020).



THE BENEFITS AND CONSEQUENCES OF A COMMUNITY COLLEGE EDUCATION

Earning a community college credential benefits students, community colleges, and their communities. Employees with a community college credential earn higher wages. A sub-baccalaureate education after high school results in long-term economic benefits, such as increased annual and cumulative earnings (Kim & Tamborini, 2019). Higher earnings result in employees who are healthier (Trostel, 2015), less likely to use social services (Carroll & Erkut, 2009), and more likely to invest in their communities (Economic Modeling Specialists, 2014). In 2012, employees with a community college education contributed $800 billion to the national economy (Economic Modeling Specialists, 2014).

Students are not the only ones to benefit financially from improved student success outcomes. Colleges benefit as well. Colleges invest resources in the classroom and in student support services. For community colleges, this investment is significant, because state and federal support of community colleges has not kept pace with these escalating resource costs (Baker et al., 2017; Fields, 2019). As funding of community colleges continues to decline, colleges may not be able to afford to maintain current student outcome levels and will need to consider the cost benefit ratio of programs that are meant to improve student success outcomes (Wild & Ebbers, 2002). For the college, improving persistence, retention, and completion are important to maintain enrollment, reduce losses, and maximize the use of resources. When community colleges implement strategies to increase retention and progression to completion, they actually reduce costs to support students who would have otherwise not completed (Johnson, 2012).

When students earn a community college credential, they enter or re-enter the workforce with the skills to make businesses more competitive and to attract new businesses and industries to a region and/or state. A skilled workforce results in higher wages leading to increased production. This increased output increases profits (Economic Modeling Specialists, 2014). When over 40% of students who start at a community college leave higher education without earning a credential, the impact affects regional and national labor markets and economies.

While persons with a community college education positively contribute to economies, there is a cost when students do not earn a college credential. As tuition and fees increase, students borrow more to cover costs. Traditionally, most community college students have not borrowed money to cover college costs. However, as state and federal funding of community colleges has decreased, community colleges have increased tuition and fees to offset this loss. As a result, more community college students are accumulating student debt by taking out loans (Baker et al., 2017; College Board, 2015; United States Department of Education, 2016b). When students do not earn a college credential, state and federal governments lose their financial investments in students in the form of financial aid and appropriations (Johnson, 2012). Over a five-year period, 2003-2008, state and federal governments spent over $9 billion on students who did not return to higher education for a second year (Schneider, 2010). When tax revenue is factored in, losses are even higher. Schneider and Yin (2011) estimate an annual loss of $730 million dollars in state and federal tax revenue is lost a year when degree-seeking students within a single cohort of students do not earn their degree within six years.

Students and families also experience losses when students do not persist and complete. In addition to the loss of the time invested in an education, when students and their families invest in college, there are opportunity costs (Sullivan, 2010). Obvious opportunity costs are the earnings students forfeit when they choose to go to college rather than working at a job that doesn’t require a college credential. Schneider and Yin (2011) estimated that for a single cohort of bachelor degree seeking students there is $3.8 billion loss of lifetime income for those who do not earn a degree in six years. However, when students take longer to complete college, transfer to another college and lose credits, or do not stay enrolled, the opportunity costs increase. When student outcomes improve, the costs to students and the associated debt decreases and prospective income outlooks increase.

NATIONAL STUDENT SUCCESS INITIATIVES

Community colleges and organizations are investing significant resources to improve student success outcomes and eliminate equity gaps in outcomes. With the guidance, resources, and partnerships of organizations and associations such as Achieving the Dream (ATD), American Association of Community Colleges (AACC), American Association of Colleges and Universities (AACU), Center for Community College Student Engagement (CCCSE), Community College Resource Center (CCRC), and the League of Innovation, there is a focus on student success initiatives to aid students in their development resulting in improved student success outcomes. Many of these initiatives, such as Completion by Design and Complete College America, support the implementation of proven practices and programming such as Guided Pathways and First-Year Experiences. These practices and programs are improving student success outcomes, as evidenced by the 2017 Aspen Award Winners (Aspen Institute, 2017). However, as ATD president Dr. Stout (2018) noted, even with these initiatives, there are still equity gaps in student success outcomes and community colleges are not improving outcomes for all students. These national initiatives address the holistic community college student experience and do not focus on success at the classroom level and the impact that has on completion. The focus needs to include students' successful completion of a class and a semester (Nutt, 2019). Students should be interacting with faculty who are pedagogues -

faculty who teach using inclusive pedagogical and active learning practices and investigate learning for the purpose of continuous improvement (Stout, 2018).

RESEARCH QUESTIONS AND HYPOTHESES

This dissertation attempts to determine if a faculty-led program, that prescribes intentional student-faculty interactions, influences community college student retention when controlling for student inputs. The program, the Persistence Project (PP), was implemented at a single, two-year public institution, Oakton Community College (Oakton). Faculty who participate in the PP commit to learning students' names within the first two weeks of class, holding one-on-one fifteen-minute meetings with each student during the first three weeks of classes during student hours, engaging students in a "get to know you'' activity (icebreaker) during the first week of class, and administering an early assessment of student learning and providing feedback within the first four to five weeks of class. These activities have been recommended by researchers as ways to improve student success outcomes (Barnett, 2011; Cole, 2007; Romsa et al., 2017) because they been shown to increase student motivation, academic success, retention, career skills development (Anderson & Carta-Falsa, 2002; Cotten, & Wilson, 2006; Guerrero & Rod, 2013; Meyers Hoffman, 2014), and student satisfaction with the institution (Romsa et al., 2017)

Many of the studies related to student attrition, retention, and persistence have focused on student departure and involvement theories and student characteristics, and their relationships to student outcomes predominantly at four-year, residential institutions. These studies are difficult to apply to community colleges because the typical community college student is part-time, older, working, and may experience breaks in their academic progress (Bailey & Alfonso, 2005).

Decades of research highlight the importance of student-faculty interactions in the academic and social development and integration of college students and outcomes at four-year institutions (Newman et al., 2015). However, few studies focus on specific strategies to intentionally increase the frequency and quality of student-faculty interactions to improve student success outcomes (Newman et al., 2015), particularly during the critical transition period to college.

Much of the research on student-faculty interactions focuses on self-reported frequency and to some extent the nature of student-faculty interactions. There have been more studies published in the last decade on the influence of student-faculty interactions on community colleges student success outcomes. However, few studies have looked at intentional ways for faculty and students to interact in and out of the classroom to improve student outcomes. This quasi-experimental study examines retrospective observational data to determine if participation in the PP influences retention of first-time in college, traditional -aged community college students by answering the following questions and associated:

1. Does participation in the Persistence Project influence term (fall) to term (spring) retention of first-time in college, traditional-aged students?

    $H1_0$: Participation in the Persistence Project does not significantly influence term-to-term retention of first-time in college, traditional-aged students.

    $H1_a$: Participation in the Persistence Project significantly influences term-to-term retention of first-time in college, traditional-aged students.

2. Does participation in the Persistence Project influence year (fall) to year (fall) retention of first-time in college, traditional-aged students?

$H2_0$: Participation in the Persistence Project does not significantly influence year to term retention of first-time in college, traditional-aged students.

$H2_a$: Participation in the Persistence Project significantly influences year-to-year retention of first-time in college, traditional-aged students.

As there are few studies that look at the impact intentional student-faculty interactions have on community college student retention, a statistical examination of such a model is warranted. For this quasi-experimental study, framed by Astin's input-environment-outcome impact model, I use propensity score analysis to control for student inputs to determine the impact a project to intentionally increase student-faculty interactions has on the retention of first-time in college, traditional-aged students.

CONCEPTUAL FRAMEWORK AND OVERVIEW

Astin uses the input-environment-outcome (I-E-O) college impact model to measure the influence of the college environment on student outcomes. This model aligns with Astin's theory of involvement which posits that the level of student involvement is influenced by the policies, practices, and programming that faculty, staff, and administrators create to engage students. The I-E-O model is composed of three components: inputs, environment, and outcomes. And, unlike earlier student integration and involvement models, Astin's input-environment-outcome (I-E-O) model considers student characteristics or inputs, such as student attributes, past experiences and educational background that students bring to college, and how they interact with the environment created by the institution. Astin states that student inputs directly influence student outcomes and interact with the institutional environment to indirectly influence outcomes. The environmental component of the I-E-O model considers all of the academic and social experiences a student has while in college and how they influence cognitive and affective outcomes associated with student development. The college environment the student is exposed to, like facilities, courses, academic, social, and support programs, and peer, faculty, and staff interactions, is controlled by faculty, staff, and the institution to support student involvement and development. The environment can interplay with student inputs to influence student outcomes.

The final component of the model, outcome, accounts for the goals of the educational initiative and associated student performance at a specific point in time (Astin, 1984; Astin & Antonio, 2012). Outcomes are the measurable abilities and skills an institution is attempting to develop during a students' college experience (Astin & Antonio, 2012). Outcomes may include students' knowledge, retention, persistence, academic standing, reasoning, logic, application, decision-making, beliefs, values, interpersonal relationships, institutional and educational satisfaction, and goals (Astin & Antonio, 2012; Pascarella & Terenzini, 2005).

Student Retention Inputs

A number of student demographic and pre-enrollment characteristics, inputs, can influence student retention and persistence, including parents' educational attainment, first generation status, family income or Pell eligibility status, gender, race/ethnicity, high school attended, age, aspiration (e.g., degree versus certificate-seeking; undecided versus identified area of interest), social and behavioral patterns and habits, academic preparedness and experiences as measured by high school grades and standardized and placement test scores (Astin, 1985; Astin, 1999; Dika, 2012). A student's perception of an institution before they even enroll in the institution, which is influenced by family and friends, can also influence their decision to stay in college.

Influence of the Student Experience on Success

The environment students experience when they start college can influence their success. The academic and social environment an institution creates can result in learning environments in and out of the classroom that provide opportunities for students to engage with faculty, staff, and peers and to acquire the knowledge, skills, and competencies they need to be successful. A review of decades of empirical studies and theoretical models, which look at causal connections between academic and social integration and the decision of a student to stay or leave an institution of higher education, indicates there is enough evidence to suggest that integration is critical to student retention (Pascarella & Terenzini, 2005).

Student engagement is also referred to in the literature as integration, involvement, and social belonging (Astin, 1999; Alicea et al., 2016; Tinto, 1993; Zepke & Leach, 2010b). Student involvement is the time and energy students devote to and actively participate in meaningful educational activities, in and out of the classroom, that are intentionally created by institutions to integrate students academically and socially (Astin, 1995; McCormick et al., 2013). Involvement can be measured by the amount of time and energy spent studying, the quality of interactions with peers, faculty, and administration, and the ability to apply new knowledge to authentic situations (Astin, 1995; Pace, 1998). Student involvement is critical to student learning and success and to improving the quality and effectiveness of a college education (McCormick et al., 2013). The first year of college is a critical time to engage students with the institution because it is the most decisive time for first-year college students.

Student-faculty relationships, with faculty as the drivers of student engagement, are a critical component of a student's transition to college and their involvement in the academic and social environments of the institution. When students experience a sense of belonging, a feeling of connectedness to others, they have higher self-esteem and college and educational satisfaction, lower social isolation, increased academic success, and increased retention (Booker, 2016; Bowman & Denson, 2014; Cotten & Wilson, 2006; Han et al., 2017; Newman et al., 2015). Students have identified positive experiences with faculty as a factor in their sense of belonging. Specifically, students identify impactful faculty as those who care about their success and perspectives, set clear expectations, create classroom environments that are safe for discussions, incorporate active learning and collaboration (Kuh et al., 2004; Wilson & Gore, 2013), believe their students belong in college, and value students' contributions and presence in class (Newman et al., 2015). According to Kinzie et al. (2008), sense of belonging is one predictor of retention for minoritized students that can be controlled by the institution. As students transition to college, they need an impactful event within the first six weeks of college that triggers a sense of belonging (Palmer et al., 2009). Engaging educational practices, such as active learning, collaboration with peers, prompt feedback, and student-faculty interactions increase sense of belonging (Kinzie et al., 2008).

Substantive interactions with faculty that extend beyond the classroom result in student cognitive and social development and increased academic achievement, institutional satisfaction, student retention, educational aspirations, and completion (Kuh & Hu, 2001; McCormick et al., 2013; Pascarella et al., 1978). Substantive student-faculty interactions are meaningful, high-quality interactions where faculty and students engage in discussions outside of class related to a course or research project, academic performance, career advising, assessment feedback, and personal matters and/or goals (Cole, 2008; Cox et al., 2010; Kuh &

Hu, 2001). The effect of student-faculty interactions remains even after confounding variables, such as pre-enrollment academic factors and student demographic characteristics, are controlled (Pascarella & Terenzini, 2005). These interactions assist students in their transition to college and the new norms students will experience, promoting a connection between the student and the institution.

First-time in college students transitioning from high school to college norms and expectations can experience difficulty integrating successfully into this new environment. This is a critical time in a students' transition period and provides an opportunity for the institution to engage students in and out of the classroom so that students feel a sense of belonging and connectedness to the institution, influencing their decision to stay or go. Faculty teaching first year students have the greatest opportunity to influence students' behaviors related to engagement by incorporating effective educational practices (Kinzie et al., 2008). Since community college students spend most of their time on campus in a classroom, their engagement with faculty and peers and with high impact practices is crucial to their learning, development, and academic and social involvement. Faculty improve learning, success, and student satisfaction through curriculum design, pedagogical strategies, and extended student-faculty interactions outside of the classroom (Cotten & Wilson, 2006).

Researchers using student-faculty interactions as an environmental variable within the framework of Astin's IEO model demonstrated that informal interactions with faculty resulted in increased satisfaction with the institution, academic progress towards goals, and participation in cultural activities (Endo & Harpel, 1982). Students identify positive teaching and learning environments resulting from quality student-faculty relationships as open, supportive, collaborative, comfortable, respectful, enjoyable, and nonthreatening. Community college faculty can provide opportunities to validate students and their experiences by being supportive and affirming and implementing teaching and learning processes that authenticate students' self-worth and learning capabilities (Rendon, 1994). These opportunities can occur in and out of the classroom and include: learning students' names, working one-to-one with students, providing encouragement and support, providing useful feedback, and creating an active and collaborative learning environment. Initiatives to improve retention of community college students should focus on the classroom because of the opportunities for student-faculty interactions (Hutto, 2017). Oakton's PP intentionally engages students with faculty in and out of the classroom during the first six weeks of classes to improve student retention.

Oakton Community College Persistence Project

In response to low fall-to-spring, within-year retention, and fall-to-fall student retention rates, Oakton developed and implemented the Persistence Project (PP). The PP is a faculty-driven project based on Odessa College's successful Drop Rate Improvement Program, which creates intentional opportunities for faculty and students to engage in and out of the classroom. Faculty participants in the PP commit to learning students' names within the first two weeks of class, holding one-on-one fifteen-minute meetings with each student during the first three weeks of classes during student hours, engaging students in a "get to know you'' activity (icebreaker) during the first week of class, and administering an early assessment of student learning and providing feedback within the first four-six weeks of classes. Since the implementation of the PP in Spring 2016, Oakton's fall-to-fall retention rates have increased from 45% to 51.4%. The Survey of Entering Student Engagement (SENSE) benchmark results for engaged learning, one of the fundamental elements of student engagement during the first three weeks of the term, increased from 44.8 to 54.8 (CCCSE, 2019). Oakton's 2019 SENSE survey results for the engaged learning benchmark were higher than its Achieving the Dream (AtD) peers, which was 52.1. Yet, Oakton's engaged learning benchmark of 54.8 was lower than the benchmark for the top 10% of the three-year SENSE cohort, which was 65.9. Collectively, students enrolled in a class where the faculty member implements the PP experience double digit increases in fall-to-spring retention rates and significantly higher fall-to-fall retention rates as compared to students who were not in a participating class.

These improved retention rates do not consider student characteristics and pre-college academic abilities (inputs), or confounding variables, which have been identified as predictors of student retention in college (Astin, 1999; Braxton et al., 2011). These numbers also report on all students who participate in the project and do not account for other plausible explanations for the increases in retention, such as a mandatory new student orientation (NSO), which was implemented at the same time as the PP. This quantitative study uses propensity score analysis (PSA) to estimate the causal effect of the treatment, the PP, on student term-to-term and year-to-year student retention for first time in college, traditional-aged students. PSA balances covariates to create similar treatment and control groups of students to determine a causal effect of a treatment when participants are not randomly assigned to the treatment. This produces a compelling estimate of treatment effects (Porter, 2020; Tanner-Smith & Lipsy, 2014). Propensity score analysis decreases the likelihood that student characteristics or factors might be responsible for any correlation between the covariates and the outcome, thereby allowing for a clearer understanding of how the PP affects retention.

Student Retention Factors

The factors that influence retention, a student's decision to stay or leave college, are convoluted (Harper & Quaye, 2014) and varied depending on several external factors and academic and social supports (Astin 1985; Crisp & Mina, 2012). There is a wide array of reasons that students do not persist from term to term or year to year while in college, including poor academic performance, poor understanding of their academic self (Meyers Hoffman, 2014), lack of financial support (Strauss & Fredericks Volkwein, 2004), failure to thrive socially by not making connections with peers or faculty (Astin, 1985; Harper & Newman, 2016; Lillis, 2011; Tinto, 1975; Tinto, 1993), or having different cultural, social and intellectual attitudes and beliefs, poor transition to college, and/or the goals of the student may not warrant completion or persistence (Tinto, 1993).

Those students who attend predominantly White institutions (PWIs) of higher education and identify as racially and ethnically diverse experience additional barriers to a successful transition. African American students at PWIs may have difficulty adjusting socially. Impediments to their transition include discrimination, isolation, alienation, lack of institutional recognition and support, and inadequate institutional fit (Love, 2009). Student inputs, such as demographics and characteristics, must be considered and controlled before measuring the effects of the environment on student success outcomes (Astin & Antonio, 2012).

Students are more likely to persist from term to term within their first year of college when they are socially and intellectually involved with the college and are motivated to expend energy on that involvement (Astin, 1999; Chickering & Reisser, 1993; Milem & Berger, 1997). Students' academic and social development as they enter college, and the opportunities they engage in, will further develop their identity and impact their retention through the first year of college. Two factors critical to student retention and development are very early academic and social involvement (Milem & Berger, 1997) and early and ongoing involvement with faculty (Liu & Liu, 1999; McClenney & Arnsberger, 2012; Milem & Berger, 1997) to direct students to services and resources, including people.

DEFINITION OF TERMS

To establish a common understanding of the terms, the following definitions are provided:

Attrition: Exit from higher education before earning a degree or certificate.

Completion: Earning a degree or certificate at an institution of higher education.

Persistence: Measurement of students' continued enrollment at any institution of higher education.

Retention: Measurement of students' continued progress at an institution of higher education, measured by term-to-term and year-to-year enrollment at the same institution.

Sense of Belonging: An individual's perceptions of attachment, group membership, and importance in an educational context.

Student Engagement: The amount of physical and psychological effort and energy exerted by students towards academic, personal, and social development while in college (Astin, 1984).

Student Success Outcome: Indicators of progress and completion at an institution of higher education, including retention, persistence, and completion.

ASSUMPTIONS, LIMITATIONS, AND DELIMITATIONS

Assumptions

I identified propensity score analysis (PSA) as the best statistical method to control for covariates or confounding variables that might influence the treatment or outcomes. Observational studies were done on the nonrandomized data. PSA balances covariates to create similar treatment and control groups of students to determine a causal effect of a treatment when participants are not randomly assigned to the treatment producing a compelling estimate of treatment effects (Porter, 2020; Tanner-Smith & Lipsy, 2014). PSA decreases the likelihood that student characteristics or factors might be responsible for any correlation between the covariates and the outcome. Differences between matched treated and control groups can be attributed to the treatment effect rather than the differences in student demographics or academics (Mertes & Hoover, 2014).

There are two assumptions made when using propensity score analysis as a statistical method. According to Rosenbaum and Rubin (1983), the researcher must assume assignment to a treatment can be ignored because all measurable covariates that affect treatment assignment and the outcomes have been included in the study. This assumption is similar to assumptions made when using regression analysis (Austin, 2011a). The second assumption is that every participant has a nonzero probability of being in either treatment group. For this study, students have the same chance of being a nonparticipant or a participant in the PP because PP specific courses are spread across the curriculum. Students do not know if they are enrolling in the PP when they choose a course, section, or faculty member.

Limitations

This study takes observational, nonrandomized data and attempts to mimic a randomized study; however, unlike a randomized study, not all the observed and unobserved covariates are balanced. Propensity score analysis reduces selection bias, but it does not eliminate it because all of the covariates (inputs) cannot or were not accounted for or measured, such as the psychological characteristics or perceptions of students that may influence retention. Another limitation of this study is volunteer bias. Faculty who implement the PP volunteer to be a part of the project. Individuals who volunteer may be different from the general population; as a result, this may challenge the external validity of this study (Salkind, 2010). Finally, some of the data on student attributes were self-reported, including student age, gender, ethnicity, and parents' educational attainment.

Scope and Delimitations

I looked at project data from a single community college making it difficult to generalize to other institutions of higher education. The study population and sample were limited to first-time in college, traditional-aged students. This student demography was chosen for several reasons. First, this group of students is required to attend new student orientation at Oakton that includes an in-person component. This is not true of all student age groups at Oakton. College is a new experience for these students. How these students respond to this new experience will influence their social and academic involvement in the life of the college and ultimately their commitment to the institution and their goals. New support systems, including faculty relationships and interactions, will influence their decision to stay. The majority of Oakton's student population, 45%, are first-time in college, traditional-aged students and 66%

are 24 or younger (National Center for Education Statistics, NCES; 2021). To broadly impact retention at Oakton, the FTIC, traditional-aged student population can be a target for participation in the PP.

CHAPTER SUMMARY

As community colleges continue to identify and implement strategies to improve student success outcomes, such as retention and completion, they will positively impact the social, personal, and economic aspects of students' lives and benefit the economic and social aspects of their communities. Current national student success initiatives that holistically address student needs as they enter, navigate, grow, and transition in, through and out of community colleges can be enhanced with the integration of intentional opportunities for students and faculty to engage with one another in and out of the classroom. Oakton's PP is one initiative that creates these opportunities. This quasi-experimental study measures the influence the Project has on student within-year and year-to-year retention by using Propensity score analysis to control for student inputs that influence retention. Framed within Astin's input-environment-outcome impact model, this study determines if first-time in college, traditional-aged students who participate in the PP are more likely to return to Oakton after participation in the Project than students who do not participate in a PP class.

CHAPTER 2: LITERATURE REVIEW

INTRODUCTION

Community colleges committed to student success for all learners will create scalable, quality, inclusive, strategic initiatives and programs in and out of the classroom that must require student involvement in the social and academic environments of the college. These inescapable opportunities should be coordinated so that students are able to make the transition to college by feeling welcomed, respected, valued, and that they belong. Ultimately, implementing initiatives focused on the holistic development of a student will improve outcomes for all students and eliminate equity gaps. Holistic approaches to student success must include opportunities for intentional student-faculty interactions. Increasing these interactions have been recommended as a way to improve student motivation and outcomes (Komarraju et al., 2010; Trolian et al., 2016); and, based on a review of the literature by Felton et al. (2016), student-faculty interactions have been identified as critical to a student's motivation, sense of belonging, engagement, and academic decision-making.

As colleges set institutional priorities to improve student success outcomes, increasing student-faculty interactions in a student's first year at the institution, must be implemented as a way to improve completion through increased student retention. Faculty play an important role in retention so initiatives to improve retention should focus on the classroom, regardless of faculty status at the college (Hutto, 2017). Student-faculty interaction is one of Chickering and

Gamson's (1987) seven principles for good practice in undergraduate education. These principles of good practice – student-faculty interaction, collaborative learning, active learning, expeditious and constructive feedback, engaged-time, high-expectations, and exposure to diverse talents and perspectives – have been positively linked to gains in self-reported learning and development. Engagement in these principles at two-year colleges results in increased retention and completion (McClenney & Marti, 2006). The literature review focuses on the importance of the college environment intentionally created by faculty, staff, and administrators to involve students and its roles in first year in college student retention.

CONCEPTUAL FRAMES

Student retention, a student's decision to stay enrolled at the college they started at term to term and year to year, has been framed within theories and models and studied by researchers and educators for decades. While many of these studies have been conducted at four-year, residential colleges and universities, more recent research has looked at the applicability of these models at two-year public institutions of higher education with mixed findings. These models typically do not address the diverse characteristics and mission of community colleges or the community college experience (Crisp & Mina, 2012). I review two primary student retention models: Tinto's model of individual student departure and Astin's theory of student involvement. I use Astin's input-environment-outcome impact model as the framework for this study because the environmental factor is an intentional community college PP to increase within-year and year-to-year student retention.

Tinto's (1993) model of individual student departure frames students' decisions to stay at or leave an institution of higher education on the quality of student effort, student perceptions of the institution, and the pre-college resources and characteristics a student brings with them to college, including demographic variables and academic characteristics. Pre-enrollment characteristics determine how a student interacts with the institution which in turn determines academic outcomes, including academic performance, retention, completion, or persistence to another institution of higher education. In a study of first-time, full-time students, Tinto identified certain institutional and student pre-entry characteristics that influence student retention and completion. The characteristics that positively influenced outcomes included higher standardized test scores, higher retention at a four-year institution of higher education as compared to a two-year institution, and higher retention at a private two-year institution versus a two-year public institution. A student's academic and social transition to college, determined by their pre-entry characteristics and efforts, influences their academic and social integration, which influences students' commitments to the institution and to their goals, and ultimately affects retention and completion (Tinto, 1993).

According to Tinto, the more integrating academic and social encounters a student engages with, their involvement and commitment to the institution increases because they perceive that the institution cares about them and supports them, resulting in positive academic outcomes. In 2000, Tinto recognized that his model and other theories of departure fail to address the classroom experience in retention and that not all student involvement leads to learning and retention. After a study of the positive effects of learning communities on student learning and retention, Tinto concluded that faculty can create classroom learning environments that promote student engagement in and beyond the classroom. Student-faculty interactions can influence student commitments and diminish the effects of pre-entry characteristics on student retention.

Astin's theory of student involvement is similar to Tinto's model. However, Astin's theory postulates that students' involvement is measured by their behaviors, measurable actions such as the amount of time and physical and psychological energy they invest in different academic and social activities and their interactions with the environment the college creates for intentional engagement (Astin, 1984; Astin, 1999). Astin makes four other assumptions about student involvement. First, the time and energy a student invests fluctuates and varies by activity. Secondly, a student's involvement includes qualitative and quantitative elements. Next, the quality and quantity of student involvement is directly proportional to student academic and personal development. Finally, Astin posits that the effectiveness of educational processes correlates to the strength of educational policies, pedagogical practices, and programs that intentionally increase involvement (Astin, 1984; Astin, 1999). Astin asserts that it is the student's responsibility to become involved while in college; it is also the institution's responsibility to create an environment that provides a wide range of academic and social engagement opportunities for students in and out of the classroom to improve their outcomes.

College employees, faculty, staff and administrators, are responsible for creating an engaging environment, through policy, programming and practice, to involve students in the life of the college, in and out of the classroom. Astin (1975) conducted a qualitative longitudinal study that identified factors that influence student retention. Astin (1975) was able to correlate each positive factor of student retention to increased student involvement, while each negative factor was connected to decreased student involvement. Astin identified environmental conditions that positively influenced involvement of four-year college students, including residence on campus, engagement in extracurricular activities, and part-time employment on campus.

This early study revealed that students at two-year colleges were less likely to return to college the following year than students at four-year colleges. Poor two-year college student retention remained when student entry characteristics were controlled. Astin attributed poor community college student retention to lack of student involvement due to external obligations, low enrollment intensity, and few student-faculty interactions (Astin, 1984; Astin, 1999). In Astin's study, student-faculty interactions are strongly related to students' satisfaction with the institution - more so than any other student or institutional characteristic.

Milem and Berger (1997) conducted a longitudinal study of first-time in college, full-time students at a private, highly selective university that combined Tinto's model and Astin's theory. Milem and Berger looked at both student perceptions and behaviors to predict institutional commitment and intent to return to the institution. Interestingly, academic integration, while critical to Tinto's model, did not predict institutional commitment or intent to persist. Social integration was a positive predictor of institutional commitment and intent to return. Milem and Berger believe their model demonstrates how student involvement early in the first year positively influences students' perceptions about the institution, which in turn, increases students' commitment to the institution. This in turn, results in students choosing to return to college the following fall.

Astin’s input-environment-outcome (IEO) impact model is used to assess the effectiveness of the college environment, including activities that influence student involvement. This model demonstrates the interaction between student inputs, the environment, and outputs. Astin and Antonio (2012) state that “outputs must always be evaluated in terms of inputs” (p. 19) because the students of different institutions of higher education vary so much. Studying only inputs and outputs without understanding how the environment influences outputs limits its practicality. The college environment, the activities and experiences a student is exposed to and interacts with, is necessary information when evaluating educational impact or effectiveness of a program or policy on student outcomes, such as student retention. Studies that use this conceptual approach focus on program, practice, and policy elements that college faculty, staff, and administration have some control over when trying to demonstrate how the college environment influences student development (Pascarella & Terenzini, 2005).

Student inputs may include student pre-enrollment student attributes and academic characteristics such as age, gender, race/ethnicity, high school grade point average, and English and math placement. Astin and Antonio (2012) also call the inputs the independent variables or control variables. In the IEO model, there is a relationship between inputs and outputs and between inputs and the environment. Astin and Antonio assert that student inputs influence the relationship between environment and outputs. Using the IEO model as a study design allows researchers to measure individual student input characteristics and “then correct or adjust for the effects of these input differences in order to get a less biased estimate” (Astin & Antonio, 2012, p. 23) of treatment effects on student outcomes.

Astin defined the environment as the student experiences that faculty, employees, and the administration create through policy, practices, and programming. The environment is also referred to as treatments, practices, programs, or interventions. Astin was interested in how the environment influences student growth or development as identified in the outputs, such as student retention. The literature review will focus on the environment, specifically intentional student-faculty interactions as part of Oakton's PP, and the impact on retention.

The outputs are the dependent variables and are referred to as outcomes and goals. The outcomes are the measurable facets of student development that the college seeks to impact or influence by the student experiences it creates with its policies, practices, or programming. Astin and Antonio identified two types of outcomes, cognitive and affective. Both can be measured using psychological and behavioral data. Student retention is a cognitive outcome measured with behavioral data such as continued enrollment and completion.

The IEO model has been primarily used in natural experiments. Astin and Antonio (2012) define natural experiments as those that study differences in environmental conditions that are not constrained by the methodology of true experiments. This allows researchers to estimate the effects of the treatment using multivariate statistical analysis. However, a serious limitation of using this model to study the effects of environmental conditions on student outcomes is that subjects are not randomly assigned to the treatment or control groups. As a result, student inputs may not be similar between the treatment group and those exposed to a different environment (Astin & Antonio, 2012). The IEO model recognizes the influences student inputs have on the environment and the outcome and provides an opportunity to control for the different student inputs reducing selection bias and creating comparable treatment and control groups. I used propensity score analysis (PSA) to equalize measurable participant characteristics, student inputs or covariates that can influence the outcomes of those in the treatment with a nontreatment group. I discuss the use of PSA as the methodology for this study in Chapter 3.

Environment

The college environment students interact with when they are at college will influence their academic and social involvement, and ultimately their retention and completion. According to Astin, to accurately assess student outcomes, student inputs, outcomes and environmental data must be analyzed because student inputs directly influence the outcomes and indirectly influence outcomes via the environment (Astin, 1991). Early student involvement with the institution and with faculty influences students' commitment to the institution and their intent to return to the institution (Milem & Berger, 1997). The optimal environment to engage students to improve retention for community college students is in the classroom.

For community college students, the classroom environment is critical because, for many, this may be the only time to interact with faculty and peers (Tinto, 2000). There are less opportunities for engagement of community college students as compared to four-year college students. Community college students are less likely to engage in extra- and co-curricular activities and with academic and student support services because of their varied obligations outside of the classroom (Alicea et al., 2016). The classroom provides a realm for academic and social interactions and a portal to extra- and co-curricular activities and academic and student support services. Faculty can create learning environments that prompt students to willingly interact with faculty outside of the classroom (Tinto, 2000). Studies have shown that it is the quality, not necessarily the quantity, of these interactions with faculty outside of the classroom that influence retention (Anderson & Carta-Falsa, 2002; Clark et al., 2002; Cole, 2008; Cotten & Wilson, 2006; Dika, 2012).

Student-Faculty Interactions

Faculty are a vital college resource that directly impact student development, learning, success, and satisfaction. How faculty interact with students in and out of the classroom, design the course curriculum, and select and deliver course content, are major aspects of the college experience (Cotten & Wilson, 2006). When faculty engage students in a warm and informal manner, grade point averages increase, and students consider educational aspirations beyond their original goal because the student admires the faculty.

Faculty, as agents of socialization, provide a pathway to college information and resources when they interact with students (Dika, 2012). Positive and supportive student-faculty interactions provide students with faculty or social capital. Faculty capital, measured by the perceived level of the faculty member's emotional and academic support and availability, improves student self-efficacy, influencing course success (Brouwer et al., 2016) and sense of belonging (Broomen & Darwent, 2014). Dika (2012) asserts that student-faculty relationships are a form of social capital that assists students in maneuvering and succeeding in college. Student-faculty relationships provide additional opportunities for students to gain knowledge and access support services that they might not have been able to without these social agents (Dika, 2012). Chang (2005) states that as students establish social capital through their interactions with faculty, this further reinforces or modifies previous student dispositions that may make them more likely to engage with faculty. Hommes et al. (2012) also link students' networks or complex interlacing relationships and their engagement in these relationships and associated opportunities to students' behaviors that result in increased learning and achievement.

Transitioning from high school to college environments and integrating successfully into the college environment can be difficult. Students typically have high personal expectations and want to be successful in college. However, students face several challenges during their transition. They may experience financial challenges that require them to work which limits their semester and annual credit loads, and interactions with peers and faculty (Thompson, 2001). It is during this crucial time that students are making the decision to stay or go. Social and academic integration, encouragement, and support were identified by Crawford Sorey and Harris Duggan (2008) as significant predictors of retention in first-time college students. Critical relationships with faculty, peers, staff, and with the institution in the first year will influence affective commitment — an emotional connection that includes a sense of belonging to and engagement and confidence with the institution (Lay-Hwa Bowden, 2013).

Achieving critical milestones and educational goals are a barometer of a student's academic and social integration into the college environment and the commitment of the institution to the student's development and well-being. College exposes traditional-aged college students to new experiences. Students' perceptions of and responses to these experiences will determine how well students transition from their traditional support systems to new support systems and how well they navigate and adjust to the new learning and social environments (Astin, 1995; Lay-Hwa, 2013). The beliefs, values, and attitudes they entered college with will be challenged. Students who transition to college successfully develop academically and socially and integrate into these environments. This is apparent in the quality of their involvement in formal and informal educational experiences and activities (Astin, 1984; Pace, 1998; Pascarella & Terenzini, 1979).

O'Keeffe (2013) reviewed data from studies conducted at institutions of higher education in the United States and Australia. His review reinforced the importance of first-time college students connecting with at least one person (faculty, staff, student mentor) at the institution to increase retention, satisfaction with the institution and college life, academic and social development and integration, and personal development. When students first arrive at college, they are highly motivated, but their success and development will be impacted by the relationships they form with faculty, staff, peers, and administrators (Chambliss & Takacs, 2014). Positive relationships increase motivation (Jaasma & Koper, 1999; Trolian et al., 2016), which will influence students' integration and satisfaction with the institution.

The impact of positive relationships with faculty, peers, staff, and with the institution may assist African American students as they transition to college, particularly at PWIs. African American students experience additional challenges when transitioning to PWIs such as harassment, inhospitable learning environments, exclusion, disrespect, resulting in low retention and persistence (Booker, 2016). Sense of belonging, increased student satisfaction with college, and student institutional fit may be mitigated resulting in increased student retention for students of color when students develop support systems with faculty, peers, staff, and student organizations (Bowman & Denson, 2014). Bowman and Denson created, tested, and validated a Student-Institution Fit instrument (SIFI) to measure students' perceptions of institutional fit since it has been identified as a leading factor in student departure. The SIFI measures students' perceptions of academic, social, cultural, physical, athletic, religious, socioeconomic, and political areas of the college experience. Several of these are related to activities in Oakton's PP, including peer-peer interactions, academic standards and expectations, and sense of community. The results of Bowman and Denson's (2014) study indicated that students who reported increased college satisfaction experience lower social isolation and increased retention.

Booker conducted a qualitative study to examine how sense of belonging and classroom environment influence the retention of undergraduate African American female students at PWIs. Booker concluded that faculty can either promote or block a sense of belonging. Faculty that interacted with students outside of class were characterized as excellent professors, accessible, and approachable. Specifically, the students stated that the faculty that influenced their retention were accessible in and out of the classroom, were engaging, responsive, and authentic, and used varied teaching styles and pedagogical methods that incorporated real-world scenarios (Booker, 2016).

Colleges are obligated to assist in students' transition to college and to help manage the associated anxiety and nervousness that comes with this transition. Colleges are responsible for creating a comfortable learning environment with opportunities for students to interact with one another, employees, and the community so they feel as if they belong, form an attachment to the institution, and become more committed to their goals (Wirt & Jaeger, 2014). Colleges that create policies and practices that intentionally engage students and direct how students spend their time and energy will influence student effort and involvement (Astin, 1984; Jacoby, 2014; Pace, 1998).

Faculty practices can increase student involvement. When faculty set high expectations and standards, incorporate active and collaborative learning, and display behaviors that demonstrate preparedness, approachability, availability, and that they care about and support students, student engagement (Bryson & Hand, 2007; Jankowski, 2017; Kuh et al., 2006; Kuh et al., 2004; Mearns et al., 2007; Reason et al., 2006) and success outcomes improve (Umbach & Wawrzynski, 2005). This is critical in a community college setting where students are less likely to participate in extracurricular activities and use campus academic and student support services due to obligations outside of the classroom (Saenz et al., 2011; McClenney & Marti, 2006). It is difficult for community colleges to provide opportunities outside of the classroom to accommodate students' challenging external schedules and obligations (Harper & Quaye, 2014). As a result, what happens in the classroom, is critical and may be the only chance to engage community college students academically, relationally, and cognitively (Alicea et al., 2016; Barnett, 2011; Liu & Liu, 1999; McClenney & Marti, 2006).

At a community college, faculty commit 90% of their time to teaching (Provasnik & Planty, 2010). Faculty need to recognize their role in a students' success and not expect that students' success is dependent solely on students' abilities and work ethic (Micari & Pazos, 2012). Faculty roles with students are varied and include teacher, role model, employer, advisor, and resource (Chang, 2005; Cole & Griffin, 2013). In these roles, faculty can create and embed intentional student engagement activities, including formal and informal student-faculty interactions. Intentional student engagement activities are evidence-based interventions that positively impact student learning and development (McCormick et al., 2013; Koljatic & Kuh, 2001). Colleges that create intentional opportunities for engagement have students that are more committed to the institution (van Herpen et al., 2019). These experiences provide opportunities for students to develop their skills to interact with peers and increase formal and informal interactions with faculty. As a result, students have an increased sense of belonging, increased first year grade point average, and an increased intent to persist (Meeuwisse et al., 2010; van Herpen et al., 2019).

Study Environment: Oakton Community College Persistence Project

This study examines the influence intentional student-faculty interactions have on the within-year and year-to-year retention rate of first-time in college, traditional-aged students at a single institution. The intentional student-faculty interactions are defined by the environment as part of Oakton's PP.

Oakton Community College, a medium-sized (5328 FTE) public two-year, high transfer, associate granting institution in northern Illinois, implemented the PP in response to low fall-to-fall student retention rates. As a result of partnership with Achieving the Dream (AtD), Oakton developed an Open Pathway Quality Initiative proposal and report, "Increasing Student Success by Building Institutional Capacity for Continuous Improvement" in preparation for its accreditation reaffirmation by the Higher Learning Commission. One of the goals within the Initiative was the PP. This is a program to increase term-to-term retention rates, a leading indicator of year-to-year retention (Phillips & Horwitz, 2017) through intentional student-faculty interactions. Leading indicators, such as term-to-term retention, course grades, grade point average, and credit load, signify student progress towards larger goals or success metrics, called lagging indicators. Lagging indicators include year-to-year retention, certificate or degree completion, and transfer and job placement rates (Phillips & Horowitz, 2017). When institutions implement programs to improve leading indicator outcomes, lagging indicators will also improve.

Oakton students' 2014-2015 overall fall-to-fall retention rate was 45%, significantly below the 54% retention rates of higher performing peers and the national average for two-year public institutions of higher education who participated in the National Community College Benchmarking Project. Oakton students provided some insight into how the institution engaged them in evidence-based strategies to support and retain new students when they completed the Survey of Entering Student Engagement (SENSE) in 2014. The SENSE measures students' perceptions about their engagement with the institution in six areas within the first three weeks of classes. One area measured by the SENSE, engaged learning, asks students to identify activities that they engaged in at least once within the first three weeks, including activities specific to their interactions with faculty: receiving prompt written or oral feedback from instructors on performance, discussing ideas or readings with my instructor outside of class, discussing an assignment or grade with an instructor, or asking for help from an instructor regarding questions or problems related to a class. Early connections with faculty and engagement with the institution lead to increased course completion and persistence to the second term (CCCSE, 2021). Oakton students' perceptions of engaged learning revealed a 2014 benchmark of 44.8, below the national average of 50.2 and of top-performing colleges, 61.3 (CCCSE, 2014).

Oakton students' perceptions of their engagement within the first three weeks of classes and Oakton's year-to-year retention rates were unacceptable. Oakton's President, Dr. Joianne Smith, set a year-to-year retention goal of 54% (Oakton, 2017). To achieve this retention goal, Oakton implemented the PP. The PP is based on Odessa College's Drop Rate Improvement program and the seven principles of good practice for undergraduate education (Chickering & Gamson, 1987). Odessa College is a public, medium-sized, associate granting, mixed transfer/career and technical institution in Odessa, Texas. Odessa's Program was developed in response to low course success rates and high course withdrawal rates (Phillips & Horowitz, 2017). The goal of Odessa's Program is to decrease withdrawal rates by intentionally creating opportunities for faculty and students to interact, thereby leading to increased course retention, success rates, and credential completion (Kistner, & Henderson, 2014). Odessa faculty that had the highest course withdrawal rates committed to making personal connections with students in one-on-one meetings at the beginning of the academic term, provide consistent feedback throughout the course, facilitate a get-to-know-you activity on the first day of class and use students' names in the first week of class, monitor students' attitudes and performance and engage students when necessary, and allow for flexibility when the need arose (Williams & Wood, 2017). Data from fall 2010, the first term the Odessa Program was implemented, through the fall of 2016 shows that course withdrawal rates decreased from 12.5% to 2% and course success rates increased from 69.8% to 80.6% (Williams & Wood, 2017). The effects of the program were consistent across all student demographic groups, including first-time in college students (FTIC). For FTIC students, the withdrawal rate decreased from 13.7% in 2010 to 2.8% in fall 2016 and course success rates improved from 61.8% to 77.4%. Odessa College also saw the number of students earning credentials increase by 55% (Kistner & Henderson, 2014). Improvements in leading indicators were attributed to students committing more time and energy to their studies resulting in enhanced performance on class assessments (Williams & Wood, 2017).

Oakton's PP was first piloted in the Humanities Department in Spring 2016 and qualitative data from both faculty and students was positive, with students believing they were supported and cared for by their faculty. Faculty reported deeper connections to their students, a better understanding of their students' needs, and a more engaging classroom environment with increased student participation. The PP was scaled up to over 120 faculty participants from all disciplines the following academic year, impacting over 2,500 students.

Faculty PP participants agree to implement the following student-faculty engagement activities into at least one of their classes each term:

- **Hold one-on-one fifteen-minute meetings with each student during the first three weeks of classes during faculty office hours.** Required office hours, are opportunities for positive student-faculty interactions outside of the classroom that have been linked to increased affective outcomes and time with faculty (Clark et al., 2002) and increased student motivation, academic success, persistence, and career skills development (Anderson & Carta-Falsa, 2002; Cotten & Wilson, 2006; Guerrero & Rod, 2013; Meyers Hoffman, 2014). Researchers have recommended that colleges create intentional opportunities for student-faculty interactions to improve student success outcomes (Cole, 2007). An institution's commitment to student-faculty interactions, a best practice (Chickering & Gamson, 1987; Kuh et al., 2010), is evident in the offering of office hours and lead to increased knowledge, completion, goal fulfillment, and success after graduation (Smith et al., 2017).

- **Learn students' names within the first two weeks of classes.** Students have identified the importance of faculty knowing their names in creating a motivating and caring classroom environment and demonstrating instructor accessibility

(Barnett, 2011; Cotten & Wilson, 2006; Eagan et al., 2012; Neville & Parker, 2019; Provitera McGlynn, 2003).

- **Engage students in a "get to know you" activity (icebreaker) during the first week of class.** Get to know you peer activities provide an opportunity for students to start making connections and get to know their peers on a personal level. As they get to know their peers, students are more likely to discuss academics and course work. These types of peer-to-peer interactions lead to increased academic performance and student development (Brouwer et al., 2016; Hommes et al., 2012; van Herpen et al., 2019; Wilcox et al., 2005). Romsa et al. (2017) recommend that opportunities for students and faculty to get to know one another and be a part of class be implemented to improve student success outcomes and students' satisfaction with the institution.

- **Administer an early assessment (e.g, quiz, written assignment, exam) of student learning and provide feedback within the first 4-5 weeks of class.** Students learn better and continue to develop academically when they receive prompt feedback on how they are doing in class (Chickering & Gamson, 1987). Students also report improved learning gains when given prompt feedback (Lundberg et al., 2018). Astin (1999) recommends that faculty review assessments with students and provide opportunities for students to reflect on the time, energy, and level of involvement in their preparation for the assessment. If the feedback is in the form of positive constructive criticism, it can aid in structuring student-faculty interactions. Cole (2008) defines constructive criticism as essential feedback that is both verbal and nonverbal and that is perceived as supportive, encouraging, and respectful. This is an opportunity for a teacher to provide prompt, useful, constructive criticism (Kim & Sax, 2010) that creates opportunities for students to improve their learning which results in improved academic performance (Cole, 2008). Romsa et al. (2017) recommend faculty provide prompt, honest feedback to students to prevent attrition.

On average, the fall-to-spring retention rate for students in the fall 2016 cohort of students in a PP class at Oakton was 24 percentage points higher than for students who did not participate in a PP class (Smith & Williams, 2021). The retention rates for Black students were even higher. Fall-to-fall retention rates for students in a PP class is not as large as fall-to-spring retention rates, but still are on average double digits (Smith & Williams, 2021).

Since the inception of the PP, Oakton students' fall-to-fall retention rates have increased from 45% to 51.4% and the 2019 SENSE benchmark for engaged learning increased from 44.8 to 54.8 (CCCSE, 2019). These intentional student-faculty interactions have demonstrated an increase in student retention for all racial and ethnic student populations at Oakton (CCCSE, 2019) and an increase in student-reported perceptions of engaged learning as defined by SENSE.

These retention rates do not consider student attributes and pre-enrollment and enrollment academic characteristics (inputs), referred to as confounding variables, which have been identified as predictors of student retention in college (Astin, 1999; Braxton et al., 2011). While there are likely equal chances students would participate in the PP or not participate in the PP, this is not clear because students are not randomly assigned to a course that is part of the PP or not part of the Project. As a result, it is unclear if there are student inputs impacting retention.

These numbers also report all students who participate in the project and do not account for other plausible explanations for the increases in retention, such as a mandatory new student orientation (NSO) that was implemented at the same time as the PP. This quantitative study uses propensity score analysis (PSA) to estimate the causal effect of the treatment, the PP, on student outcomes, including term-to-term and year-to-year student retention for first-time in college, traditional-aged students. PSA balances covariates to create similar treatment and control groups of students to determine a causal effect of a treatment when participants are not randomly assigned to the treatment. This produces a compelling estimate of treatment effects (Porter, 2020; Tanner-Smith & Lipsey, 2014). Propensity score analysis decreases the likelihood that unobserved characteristics or factors might be responsible for any correlation between the covariates and the outcome.

STUDY INPUTS

Students' intention to continue at the institution they originally enrolled in from term to term and year to year is impacted by several factors. Because the decision to stay at college or leave is not a linear decision, it is difficult to truly determine who will choose to persist (Friedman & Mandel, 2011). However, researchers have consistently identified student characteristics that influence retention. The factors or student inputs are academic pre-enrollment and enrollment characteristics and individual student attributes. According to Astin (1985), the ways in which student inputs interact with the college environment directly and indirectly influences student outcomes.

Studies and literature reviews of student retention have revealed that there are multiple factors that influence a student's decision to stay or go (Crisp & Mina, 2012; Nakajima et al., 2012). I identified measurable, evidence-based predictors of first-time in college students including educational goals and planning, enrollment intensity, gender, math and English placements, high school grade point average, race and ethnicity, Pell awarded, first generation status, and standardized test scores. The role of these factors as predictors of retention varies from study to study depending on the type of statistical methods and construct used, and if other variables were controlled for when looking at a variable's use as a factor to predict retention.

College Readiness

College readiness for this dissertation study was determined by English and math placement either into college-level or developmental courses. Studies of college readiness as a predictor of student retention look at placement and enrollment into and success in developmental college courses. In a study of four cohorts of first-time college students enrolled at a community college in Texas, Fike and Fike (2008) used quantitative methods to study retrospective data to determine predictors of within-year retention and year-to-year retention. The researchers included successful completion of and failure or withdrawal from developmental writing, reading and math courses as predictor variables in their study. A multivariate logistic regression analysis indicated that passing developmental reading, writing and math courses increases fall-to-fall retention rates. Of the three developmental courses, passing developmental reading was the strongest predictor of student retention of the three developmental courses (Fike & Fike, 2008). Students who did not enroll in developmental reading were more likely to return the following term and year, while students who did not enroll in math were less likely to return. Fike and Fike attributed the developmental reading nonenrollment with students who tested at college level reading; however, they could not provide a reason for the poor retention associated with developmental math nonenrollment.

While not universally found to impact student retention (Mertes & Hoover, 2014), math placement is a predictor of student retention. An observational study of data from three community colleges conducted by Bremer et al. (2013) identified math placement as a predictor of year-to-year student retention. Analyses of regression and logistic regression models demonstrate a relationship between math placement and retention. The higher the math placement the more likely a student is to return in the second term and second and third fall semesters ($p < .001$). Reading placement scores were marginally significant ($p < .052$) and writing placement scores did not demonstrate any relationship to retention.

Educational Goals

A student's goal, as identified by their reason for being at college, is a predictor of retention (Bean & Metzner, 1985; Voorhees, 1997). Meet (2002) conducted a study using data from two cohorts of first-time in college students enrolled at two community colleges, one in Texas and one in Illinois. Student data was collected over a four-year period. Meet conducted regression analysis to identify predictors of retention. Most students who left within the first two years did not have known educational goals, as indicated by the lack of intent or declaration to earn a certificate or degree or to transfer. Zurita's (2004) qualitative study of first-year college retention of Latinx students identified differences between persisters and non-persisters. Lack of clear educational and career goals was one of four negative attrition factors revealed in interviews with five Latinx students who dropped out within their first year at a four-year institution.

However, as seen with other studies of predictors of student retention, student goals are not always a predictor of retention (Nakajima et al., 2012). Feldman (1993) studied predictors of retention for a single cohort of first-time in community college students using Chi-square analyses and logistic regression. Whether a student was just taking a few classes, completing a certificate, or earning a degree or transferring, any significance in the Chi-square analysis was lost during logistic regression. This suggests that other factors may play a more important role in year-to -ear student retention.

For this study, educational goals were defined by the students' interest in seeking a degree or not seeking a degree and if they made an educational plan within the college's student information system or with an advisor.

Enrollment Intensity

A student's enrollment intensity, as captured by their status as a full-time or part-time student, is identified as a factor in student retention (Feldman, 1993; Nakajima et al., 2012; Seppanen, 1995; Somers & Cofer, 2000). Fike and Fike (2008) studied predictive factors of within-year and year-to-year retention of first-time in community college students. First semester enrollment intensity was identified as a positive predictor of student retention. Fike and Fike's (1993) study supported an earlier study conducted by Feldman. Feldman (1993) conducted a retention study of first-time in community college students to determine predictors of year-to-year retention. Part-time students were 2.23 times more likely to withdraw from college than full-time students (p. 511). Enrollment status as a predictor of year-to-year retention was consistent in Chi-square and logistic regression analyses (Feldman, 1993).

In this study, the research identified students as full-time if they enrolled in 12 or more credit hours each semester. Part-time students enrolled in less than 12 credit hours each semester.

First-Generation Status

First-generation college students (FGCS) are generally identified as college students whose parents did not earn a bachelor's degree. Studies have demonstrated that FGCS are less likely to persist and complete college, as compared to students who may have similar predictors of early attrition (Ishitani, 2003). Pratt et al. (2017) conducted a study of first-time, full-time college students at a four-year university; self-reported FGCS made up about 23% of the sample and were at higher risk to leave college within the first year as compared to their non-FGCS. FGCS had an attrition rate of 20% compared to 12% for non-FGCS, even when other predictors of success were considered. Pratt et al's study supported a previous longitudinal study of National Educational Longitudinal Study data of students at four-year public and private universities conducted by Ishitani (2006). First-generation students, whose parents only had a high school diploma were 8.5 times more likely to withdraw in their second year of college than continuing generation students. Students whose parents had some college experience were 4.4 times more likely to leave college. Ishitini did not control for other predictors of student retention. Other studies have demonstrated that controlling for other predictors of student retention mitigates some effects of first-generation status on retention, but it does not eliminate the impact of first-generation status on retention (Radunzel, 2018).

For this study, first-generation status was determined by students self-reporting parent educational attainment. Students with parents with less than a bachelor's degree were identified as first-generation.

Gender

Students' gender has been linked to student retention (Feldman, 1993; Voorhees, 1997). However, study results are inconsistent. Feldman conducted a quantitative study of first-time college students at a single community college to determine predictors of year-to-year retention (1993). When considered by itself, gender influenced retention. Females were more likely to persist as compared to students who identify as male. Gender as a predictor of retention was mitigated when considered in conjunction with other variables, suggesting it may have a weak or indirect influence on retention (Feldman, 1993). Windham et al. (2014) studied predictors of fall-to-fall retention for first-time-in community college students. They conducted a quasi-experimental study using retrospective data to identify pre-enrollment predictors of community college student retention and the impact of study skills courses on retention. In their study, gender was the highest statistically significant predictor of retention ($p < .001$); 94% of females were more likely to be retained than males.

Crawford Sorey and Harris Duggan (2008) conducted a mixed methods study of retention, comparing the factors that influence retention of traditional-aged and nontraditional aged first-time-in community college students. Gender was not identified as a significant factor in predicting student retention for either student group. Fike and Fike's (2008) study of first-time in community college students also did not identify gender as a predictor of within-year or year-to-year retention. After controlling for covariates, a logistic regression model to predict first fall to first spring retention and fall-to-fall retention did not demonstrate that gender was a statistically significant predictor of retention.

For this study, students self-identify gender as female, male, or choose not to respond.

High School Grade Point Average

The pre-enrollment academic characteristic, high school grade point average (GPA) is a predictor of student retention at community colleges (Dika, 2012; Feldman, 1993; Lotkowski et al., 2004; Nunez, 2015; Somers & Cofer, 2000). High school GPA was one of the few consistent predictors of fall-to-fall student retention in a study of first-time community college students conducted by Mertes and Hoover (2014). The Pearson correlation coefficient was significant for two cohorts of students, 2007 and 2010, in predicting year-to-year retention, $r = .222$, $p < .01$ and $r = .205$, $p < .01$, respectively. This study supported the study conducted by Feldman (1993) who used a Chi-square analyses, one-way ANOVA, and logistic regression to determine the relationship between retention and the pre-enrollment characteristics of first-time in community college students. In Feldman's study, high school GPA was the most significant predictor of retention. For each one-point increase in GPA, the dropout rate decreased by a factor of 0.46.

I coded high school GPA as a binary variable. For the study, students were matched based on their weighted high school GPA of greater than or equal to 3.0 or less than 3.0.

Race and Ethnicity

Race and ethnicity have been identified as predictors of student retention (Feldman, 1993; Zhao, 1999). In statistical analyses of National Postsecondary Student Aid Surveys (NSPAS) of two-year college students, researchers identified predictors of fall-to-spring, within-year retention. Variables were arranged into five categories including student background, aspirations and achievement, college experiences, current year price and subsidies, and debt load (Cofers & Somers, 2001; Somers & Cofer, 2000). In Cofer and Somers' analyses of the

NSPAS data, they identified that some ethnic and racial groups, particularly students who identify as Black or African American, are more likely to choose to not stay and withdraw from higher education. Student race and ethnicity was a predictor in a study of first-time community college students conducted by Feldman (1993). Students who identified as Black or African American were 1.75 times more likely to withdraw from college than White students (p.510). Race and ethnicity as a predictor of year-to-year retention was consistent in a Chi-square and logistic regression analyses (Feldman, 1993). As seen in other studies of student retention, ethnicity and race as predictors of student retention are inconsistent (Fike & Fike, 2008; Windham et al., 2014).

The racial and ethnic student groups in this study included Asian, Black non-Hispanic, Hispanic, Native American/Alaskan Native, Pacific Islander, and White non-Hispanic. Each racial and ethnic student group was coded as its own variable.

Socioeconomic Status

Students' financial need has been identified as a predictor of student retention (Dika, 2012: Fike & Fike, 2008; Nakajima et al., 2012). In a statistical analysis of National Postsecondary Student Aid surveys of two-year college students, Cofer and Somers (2001) identified predictors of fall-to-spring, within-year retention. Variables were arranged into five categories: student background, aspirations and achievement, college experiences, current year price and subsidies, and debt load (Cofer & Somers, 2000; Somers & Cofer, 2001). The studies revealed two of the strongest predictors of within-year retention for students enrolled in two-year institutions were low debt loads and accessibility to grants and loans. These emerged as the two strongest predictors of within-year retention when all other variables were controlled including aspirational goals as identified by degree versus nondegree seeking students, ethnicity, age, high school GPA, enrollment intensity. Students eligible for subsidies, such as grants, work study, and loans, and students with low debt loads were more likely to return the next term than those who did not have access to subsidies and who had higher debt loads.

In a quasi-experimental study conducted by Windham et al. (2014), financial aid was not a significant predictor of retention, $p = 0.663$ (2014). Windham et al. studied the retention of first-time community college, full-time students who had a reading placement score and enrolled in a study skills course. A logistic regression analysis conducted as part of this study indicated that financial aid was not a predictor of fall-to-fall student retention ($p > .001$).

For this study I used Pell awarded status as an indicator of socioeconomic status.

Standardized Test Scores

Standardized test scores, such as ACT and SAT scores, have been identified as predictors of student retention (Dika, 2012; Lotkowski et al., 2004; Robbins et al., 2006; Sperry, 2014; Windham et al., 2014). Students who scored higher on ACT tests were more likely to graduate than students who scored lower on ACT tests (Sparkman et al., 2012). Sparkman et al. conducted a mixed-methods study to determine if self-reported emotional intelligence influences academic performance, including retention and achievement. The researchers conducted statistical analyses to test the relationship between pre-enrollment characteristics, such as high school GPA and ACT scores on graduate rates within five years. An analysis of a one-way ANOVA indicated that ACT scores are a predictor of student retention and completion. A study of SAT scores also showed a correlation between scores and fall-to-fall retention.

Students who had higher SAT scores had higher first to second year retention rates than students who had lower SAT scores (Westrick et al., 2019).

In a study of freshman at a public state college, Friedman and Mandel (2011) conducted a one-way analysis of variance (ANOVA) to test if control variables and motivational factors were significantly different between student who returned to college in the fall, those students who did not return or those students that were academically ineligible to return. Standardized test scores, a control variable, did not predict student fall-to-fall retention.

SAT and ACT standardized score data was collected for this study. ACT scores were converted into SAT scores and an SAT score of 1170 was used to create a binary variable.

Study Outputs

Students leave college for a wide variety of reasons. Studying the within-in year and yearly retention of first-time college students is important because it is an early indicator of student success and provides an opportunity to identify the need for assistance and interventions (Mortensen, 2012). I discuss the importance of addressing student retention in Chapter 1.

CHAPTER SUMMARY

This study addressed the influence of a faculty-led PP on first-time in college, traditional-aged student project participants' term-to-term and year-to-year retention at a community college. The Project intentionally embeds student-faculty interactions into students' experiences as they transition to college. Prior studies demonstrate how student inputs can predict student retention. Literature also supports the importance of environmental components, such as student-faculty interactions, on students' decisions to stay at or leave an institution. Astin's input-environment-outcome impact model demonstrates how the environment created by an institution can interact with student inputs to influence student retention directly or indirectly. Community college faculty, staff, and administrators can create intentional opportunities for student-faculty interactions in and out of the classroom and incorporate these opportunities into their holistic approach to improving student success outcomes.

CHAPTER 3: METHODOLOGY

INTRODUCTION

Existing research has demonstrated that student-faculty interactions influence student retention. In this quantitative, quasi-experimental study, I used statistical methods to determine if participation in Oakton's PP, a program that creates intentional opportunities for student-faculty interaction, influences term-to-term and year-to-year retention. The methods were guided by Astin's input-environment-outcome impact model. The purpose of this study was to expand knowledge about program effectiveness at Oakton and to determine the treatment effects of the PP on the within-year and year-to-year retention of students who participated in the project using Propensity score analysis to control for student inputs that influence retention.

CONCEPTUAL FRAMEWORK

Propensity score analysis (PSA) was used to measure program effectiveness by using nonrandomized, retrospective observational data to capture study participants' two potential outcomes, one because of participation in the program and one as a part of the control condition or nonparticipation in the program (Keller & Lacy, 2013; Rubin, 1974). According to Tanner-Smith and Lipsy (2014), PSA allows researchers to create study designs that produce compelling estimates of treatment effects when true randomized controlled studies are not possible. Educational policies, programs, and interventions that are embedded within the organizational structure of the institution may make it difficult to conduct a randomized controlled study (Randolph et al., 2014; Tanner-Smith & Lipsey; 2014). PSA addresses the counterfactual outcome or missing data required to determine if the treatment impacts the outcome in a nonrandomized study (Rubin, 1974). For this study, the counterfactual outcome determines what the student's retention would be if they had not participated in the project.

Propensity score analysis can mimic randomized controlled trials by equalizing measurable participant characteristics, covariates that can influence the outcome, of those in the treatment with a nontreatment group (Gant & Crowland, 2017). Covariates are the study independent variables and are also known as confounding variables and student inputs. PSA balances covariates to create similar treatment and control groups of students to determine a causal effect of a treatment when participants are not randomly assigned to the treatment. This produces a compelling estimate of treatment effects (Porter, 2020; Tanner-Smith & Lipsy, 2014). Propensity score analysis decreases the likelihood that unobserved characteristics or factors might be responsible for any correlation between the covariates and the outcome. Differences between matched groups can be attributed to the treatment effect rather than the differences in individual attributes or academic pre-enrollment and enrollment characteristics (Mertes & Hoover, 2014).

Study participants are assigned a propensity score based on the observed covariates. The propensity score is the probability that a student will receive the treatment (program participation) based on their covariates (Faries et al., 2010) and is determined through multivariate logistic regression. The propensity score is "a single composite variable that incorporated all of the relevant covariates" (Tanner-Smith & Lipsy, 2014, p. 4). A propensity score value will be between 0 and 1 because it is a probability (Thavaneswaran & Lix, 2008). According to Astin and Antonio (2012), using propensity score analysis and multivariate regression logistic models could address the effects of input differences on the college environment (treatment) and outcomes based on their input-environment-outcome impact model of student retention.

When the treatment group is converted into an experimental data set with propensity score matching, the treatment and control groups look similar, resembling a randomized treatment (Porter, 2020). This reduces selection bias and meets the strong ignorability assumption of PSA. The assumption of strong ignorability assumes two conditions of PSA: “The first condition says that treatment assignment is independent of the potential outcomes condition on the observed baseline covariates. The second condition says that every subject has a nonzero probability to receive either treatment” (Austin, 2011a, p. 403); that is, if a study participant has a propensity score greater than zero, they have a probability of having participated in the treatment conditional upon the covariates. This assumption is met because all the measurable variables are accounted for that may affect the outcome or that may differ between treatment and control conditions (Porter, 2020).

For this study, I identified 28 measurable covariates that studies have demonstrated influence student retention. The study covariates are organized into individual student attributes and student enrollment characteristics including, the parents’ highest educational attainments as captured by the students’ first-generation status, degree versus certificate seeking, standardized exam scores, Pell awarded, high school grade point average, race/ethnicity, math and English placement, first term enrollment intensity, educational planning, and gender. The establishment of these covariates as predictors of retention is discussed in Chapter 2. I received IRB exempt approval to conduct this study on June 25, 2021, from Ferris State University (Appendix A) and on June 3, 2021, from Oakton (Appendix B).

RESEARCH QUESTIONS AND HYPOTHESES

The aim of this research was to determine the treatment effects of the PP on the study participants by comparing term-to-term and year-to-year retention of students who participated in the PP to a control group. This study was designed to answer the following research questions and associated hypotheses.

1. Does participation in the Persistence Project influence term (fall) to term (spring) retention of first-time in college, traditional-aged students?

   $H1_0$: Participation in the Persistence Project does not significantly influence term-to-term retention of first-time in college, traditional-aged students.

   $H1_a$: Participation in the Persistence Project significantly influences term-to-term retention of first-time in college, traditional-aged students.

2. Does participation in the Persistence Project influence year (fall) to year (fall) retention of first-time in college, traditional-aged students?

   $H2_0$: Participation in the Persistence Project does not significantly influence year to term retention of first-time in college, traditional-aged students.

   $H2_a$: Participation in the Persistence Project significantly influences year-to-year retention of first-time in college, traditional-aged students.

DATA COLLECTION

Individual student attributes and pre-enrollment and enrollment academic characteristics and PP participation data were retrieved from multiple sources including Oakton’s Student Information System (Ellucian Banner), Zogotech (data warehouse), student financial aid system PowerFAIDS, and the Office of Advising, Transition, and Student Success files.

A research request was submitted to the Office of Research and Planning (ORP). ORP securely placed the data in Excel files stored on a secure Oakton computer accessible only by a an ORP staff member. Student names were not included in data files. The students' Oakton identification numbers were included in data files, but I did not have access to these files. Stata software was also installed on the same computer and the data files were imported into the software to sort student covariate information to create study sample descriptives and propensity scores to conduct modeling. I hired the ORP staff member to collate the data and run the model I created. The staff member and I met regularly to discuss propensity score and covariate balancing so I could make the appropriate adjustments prior to the measurement of the treatment effects.

Missing data was handled in one of two ways. If the missing data included a small number of students as compared to the known data, the participants were removed from the study. While this may impact bias, the number of participants removed was small, thereby decreasing the bias (Ann, 2019). For variables that had a larger number of participants with missing data, another covariate was created, and data was coded as known or unknown. Coding data as known or unknown uses a missing indicator approach to estimate propensity scores which further balances observed data with missing data (Rosenbaum & Rubin, 1984). How missing data was handled for specific covariates is discussed in Data Analysis and Methods.

STUDY POPULATION

The population for this study comprises first-time in college (FTIC), traditional-aged students enrolled at Oakton for the first time in the Fall 2018 and Fall 2019 terms at Oakton. Students were 18-21 years old, earned a high school diploma or high school equivalency, and attended an institution of higher education, Oakton, for the first time in the Fall 2018 or Fall 2019. The student population was further defined by the propensity score match of students in the treatment group and students not in the treatment group. A total of 2,316 first-time in-college traditional-aged (FITC) students enrolled at Oakton in the fall 2018 and fall 2019. Of these, 1,142 enrolled at Oakton in fall 2018 and 1,174 enrolled at Oakton in fall 2019.

Data Analysis and Methods

The data analysis and methods for this study are composed of three primary components, data preparation, descriptive statistics and inferential statistics. Data preparation included identification of the study independent and dependent variables, assignment of dummy variables for use in inferential statistics, and narrowing of the study sample based on propensity score assignment, matching and balancing, and covariate balancing. Descriptive statistics, including numbers, means, and standard deviations, were captured for the study sample prior to and after propensity score calculation. Finally, inferential statistics were used to calculate and match propensity scores, evaluate the balance of the propensity scores and covariates, and to approximate the treatment effect.

Data Preparation

Variables, including individual student attributes and pre-enrollment and enrollment academic characteristic data, that are identified as predictors of retention, were used for the PSA. These independent variables are also referred to as confounding variables, covariates, and student inputs. For this study, the independent variables are referred to as covariates. In a PSA, covariates are predictive of or correlated to the outcome of the treatment effect (environment) or outcome, in this case, retention. I identified 28 covariates that were organized into two categories: individual student attributes and academic covariates. The dependent variable in the PSA is the environment or treatment, further defined as participation or nonparticipation in the PP.

Descriptive statistics of the study population, first-time in college, traditional-aged students, that started in the fall 2018 and fall 2019 terms were described by the covariates identified for this study. Once the study sample was identified by propensity score matching, descriptive statistics were provided for matched subjects in the analyses. Descriptive statistics included means, percent bias, and percent bias reduction. T tests of differences between groups was used to determine any significant difference for any of the covariates. The purpose of propensity score analysis is to reduce bias to achieve as near perfect balance as possible; however, perfect balance is not necessarily needed to determine a causal inference (Morgan & Todd, 2008).

To determine the average treatment effect to test the hypotheses, Stata treatment-effects (teffects) command was used which creates a logit model using propensity score matching estimators (Stata Press, 2013). The regression model predicts student retention if they participated in the PP and student retention if they did not participate in the PP by understanding the relationship between the independent, dependent and outcome variables. The outcome variables are fall-to-spring and fall-to-fall retention, and the treatment dependent variable is participation in the PP.

Individual Student Attributes as Covariates (Inputs)

Study population demography is used in PSA to create matches between participants exposed to the treatment with those not exposed to the program. As discussed in Chapter 2, retention is influenced by student inputs, including individual student attributes. Student attributes that have been identified as predictors of retention include first generation status, gender, Pell awarded, and race/ethnicity. Table 1 identifies student attributes and characteristics as study covariates. Categorical data were dummy coded as binary variables for a logistic regression to create propensity scores where 1 indicated the attribute was observed and 0 indicated the attribute was not observed for a study participant. Student academic covariates were assigned a dummy code for a multivariate logistic regression to create propensity scores. Student race/ethnicity was coded with exhaustive, mutually exclusive binary variables. Binary variables for missing race/ethnicity and first-generation status data were created. A complete case analysis method was used for missing data for gender. Twelve subjects, 11 from the fall 2018 cohort and two from the 2019 cohort, for which there was no gender information were removed from the study.

Table 1. Student Attributes and Characteristics as Study Covariates

ATTRIBUTES	ACADEMIC PRE-ENROLLMENT AND ENROLLMENT CHARACTERISTICS
First-generation	High school grade point average, weighted, at or above 3.0
Not first-generation	High school grade point average, weighted, <3.0
Unknown first-generation status	Unknown high school grade point average
Male	Developmental/ESL EGL placement
Female	Full-time enrollment status (12 or more credit hours in first term
Pell-awarded	Part-time enrollment status (less than 12 credit hours in first term
Not Pell-awarded	No educational plan
Asian/Pacific Islander	Educational plan
Black, non-Hispanic	Certificate-seeking
Native American/Alaska Native	Degree-seeking
White, non-Hispanic	College-level math placement
Unknown race/ethnicity	Developmental math placement
	Standardized test scores SAT below 1070
	Standardized test scores SAT at or above 1070

Note. 0 = No, 1 = Yes

Student Academic Covariates (Inputs)

Retention is also influenced by student academic and enrollment characteristics as captured by high school grade point average, major declaration, enrollment intensity, educational planning, and math and English placement as discussed in Chapter 2. Study population characteristics are used in PSA to create matches between participants exposed to the treatment with those not exposed to treatment. A code of 1 indicated the attribute was observed and a code of 0 indicated the attribute was not observed for a study participant. A binary variable for missing high school GPA data was created. A complete case analysis method was used for missing data for math placement. Fifty-one subjects for which there was no math placement information were removed from the study, 25 from the fall 2018 cohort and 26 from the fall 2019 cohort. Standardized exam scores for study participants included ACT and SAT scores. ACT scores were converted into equivalent SAT scores using the 2018 ACT/SAT Concordance Tables (American College Testing, 2021).

Dependent Variables: Environment and Outcomes

The PP is the dependent variable for PSA. It is known as the treatment condition or environment and is a dichotomous variable. Control and treatment groups were based on propensity score matching of students who participated in the PP who had a similar propensity score to those who did not participate in the PP. Participation in PP is captured with the value 1 for participation in PP and nonparticipation in the PP is coded as 0 for the control group.

A logistic regression was conducted to determine the average treatment effect to test the hypotheses. The dependent variables are the within-year and year-to-year retention rates of study participants. Students who returned in the spring were coded as 1 and those that did not return in the spring were coded as 0. Students who returned the following fall were coded as 1 and those study participants who did not return in the fall were coded as 0. Four models were created to capture the within term and term-to-term retention outcomes, two each for the fall 2018 and fall 2019 cohorts.

INFERENTIAL STATISTICS

Creating an Experimental Data Set to Study Treatment Effect

Propensity scores were estimated with a multivariate logistic regression model with Stata software. The measurable covariates are the baseline factors used within the regression model to create parity between the treatment and control groups. The propensity score (e) for each study participant or individual (i) is described as the probability (P) of assignment to a particular treatment or control group (T) given a set of covariates (X) and is expressed as ei (Xi) = $P(Ti = 1|Xi)$ (Rosenbaum & Rubin, 1983). The propensity score is a single value that is a compilation of observed covariates that indicates the probability of a subject being treated (Rubin, 2001). When treated and control subjects are matched based on propensity scores, differences in outcomes between the two resulting groups, treated and control, is not due to the observed covariates (Rubin, 2001) because the matches have similar allocation of covariates (Howarter, 2015).

Balancing Propensity Scores and Covariates Before Matching

Once a propensity score for each observation was estimated, I confirmed overlap in the spectrum of propensity scores between the treatment and comparison group. Overlap of propensity score estimates are assessed by looking at the area of common support. Common support assures the distribution of propensity score estimates, a composite of measurable covariates for each student, is similar for the treated and untreated groups (Caliendo & Kopening, 2008). I first assessed overlap in the distribution of covariates across treated and untreated groups within the area of common support by generating histograms of the propensity scores for each group. Histograms are a graphical diagnostic that provides a way to evaluate covariate balance (Benedetto et al., 2018). I used minima and maxima comparisons, a popular method in propensity score analysis (Caliendo & Kopeinig, 2008), to develop common support. The minimum and maximum values of the propensity scores in the treated and untreated groups are compared and any observations that were smaller than the minimum or larger than the maximum propensity scores for the opposite group were not included in the analysis (Caliendo & Kopeinig, 2008). This ensures that each individual in the treatment group is close to an individual in the untreated group.

Matching Propensity Scores

After a single propensity score was estimated for each participant in the study and the balance of scores was established, 1:1 nearest-neighbor (NN) with replacement and with caliper adjustment matching was conducted to pair study participants from each group. NN matching is used to pair a randomly selected treated participant with a participant from the control group who has the nearest match (Benedetto et al., 2018). NN matching with replacement allows a control group participant to be paired with more than one treatment participant. NN matching with replacement was used because there was two times more participants in the control group as compared to the treatment group. NN matching with replacement improves the quality of matches. This may further reduce selection bias because controls that are like many treatment participants can be used numerous times (Stuart, 2010). NN matching with replacement does not reduce bias as well as NN matching without replacement (1:1 matching) (Howarter, 2015) but replacement does reduce variance among matches (Stuart et al., 2009). Nearest neighbor matching with replacement allows for the best possible match of propensity scores of nonparticipants and participants increasing the number of observations in the study.

Using a caliper distance, which is a specific number of standard deviations of the logit of the propensity score, decreases selection bias and increases the match quality (Benedetto et al., 2018; Lunt, 2014). While there are no guidelines on how to choose the appropriate caliper distance for propensity score matching, recommended caliper widths range from 0.05 to 0.25

standard deviations (Guo & Fraser, 2015; Staffa & Zurakowski, 2018). According to Austin (2011a),

> Matching on the logit of the propensity score using calipers of width equal to 0.2 of the standard deviation of the logit of the propensity score and calipers of width equal to 0.02 or 0.03 tended to have superior performance for estimating treatment effects. (p. 160)

Austin's (2011a) study specifically identified the optimum caliper width that reduces bias and results in correct mean-squared errors, Type I error rates, and coverage of confidence intervals for both binary and continuous variables. Howarter (2015) conducted a study to identify the optimum caliper width for study sample sizes of less 200. A caliper width of 0.2 standard deviation reduced bias in propensity score matching by over 99% which is consistent with other studies and recommendations (Austin, 2009; Austin et al., 2007). A caliper width of 0.6 standard deviation reduced bias by over 96%. To reduce bias in this study, I used a caliper width of 0.25 of the standard deviation of the logit of the propensity score.

Balancing Covariates After Propensity Score Matching

Once the propensity scores of the treated group were matched with those of the comparison group, I ensured balance in the matched samples. It is clear in the literature that what constitutes acceptable common support, including methods and criteria, is still not apparent (Haiyan & Clark, 2019). Propensity score matching is considered a good estimator of the counterfactual outcome if covariates are balanced after multiple balance checks (Garrido et al., 2014). When covariates are balanced after matching this indicates matches are comparable (Howarter, 2015). I used histograms, percent bias in the matched groups, minima and maxima propensity score value comparisons, and standardized difference means for each covariate between matched treated and control groups.

Histograms were used to assess covariate balance after matching and these graphs were compared with the histograms of propensity score distribution before matching. Prior studies suggest that percent bias should be below 10% to ensure a good match and balance of covariates between the treated and controls (Austin et al., 2007; Stuart et al., 2009). Other authors recommend a bias of less than 5% (Grilli & Rampichin, 2011) and others indicate that above 20% is of concern (Rosenbaum & Rubin, 1985). I used a percent bias of below 10% as an indicator of balance. If bias was 10% or higher, I looked at percent bias reduction to determine how much reduction occurred between the covariate and the reference group and at the *t* test for significance. The *t* test has been identified as a controversial indicator of balance between covariates for treated and control groups after matching because if sample sizes are small, statistical power is lost which may result in an inflated *p* value (Howarter, 2015). Standardized difference of means between the matched treated and control groups measures the effect size between groups and is preferred over *t*-test results (Austin et al., 2007). I used Stata's stddiff to measure the difference in means and identified those covariates with an absolute value difference of more than 0.2 as potentially unbalanced between the two groups (Howarter, 2015; Rubin, 2001). There is a wide range of opinions on what is an acceptable criterion to determine imbalance. Ranges vary from 0.10 to 0.5. Cohen recommended using an index of criteria to determine imbalance. Standardized differences between 0.2-0.5 represent small effect sizes and indicate 85% and 67% overlap in propensity score distributions, respectively (Andrade, 2020). Values between 0.5-0.8 and over 0.8 indicate medium and large effect sizes, respectively (Cohen, 1988; Yang & Dalton, 2012). However, currently there is no accepted level to determine what is a significant difference between two groups (Austin, 2009; Yang & Dalton, 2012).

Measuring Treatment Effect

The average treatment effect was measured by determining the mean within-year and year-to-year retention rates of nonparticipants and participants in the PP for each cohort. I used treatment-effects (teffect) psmatch command in Stata to apply propensity score matching estimators in a logistic regression. The treatment effect is calculated by using the missing potential outcome for each subject and then taking the average of the subject's observed and potential outcome (Stata, 2013).

RELIABILITY AND VALIDITY

Quasi-experimental studies are subject to validity threat because of confounding variables and selection bias (Onwuegbuzie, 2000). The study methods should reduce threats to validity. Propensity score matching methods control for measurable covariates that may influence the environment or outcomes by creating a single propensity score from multiple confounding variables. However, not all covariates may be measurable or may go unobserved resulting in biased estimates and reduced internal validity (Steiner et al., 2011). It may be difficult to estimate the causal effects of the treatment if all confounding variables are not accounted for in the creation of the propensity scores. For this study, I included all student attributes and pre-enrollment and enrollment confounding variables that students self-reported or that were gathered from Oakton's systems.

Selection bias threatens internal and external validity. The study was not a randomized study which introduces selection bias and threatens validity of the study. As a result, the study cannot be generalized to other student populations. My use of 1:1 matching with replacement results in a larger bias reduction and increased covariate balance than other propensity score matching methods. Matching with replacement increases the sample size reducing the number of unmatched individuals (Garrido et al., 2014; Leite, 2016). Ensuring balance of propensity scores before and after matching further reduces bias in a nonrandomized study. Common support was created with caliper distancing and eliminating any of the observations made outside the range of common support for each model (Garrido et al., 2014).

Factors that influence the reliability of the study include self-reported data, faculty volunteer bias, and whether faculty PP participants implemented all the required components of the Project. Some covariate data was self-reported by students including student attributes such as gender, race/ethnicity, and first-generation status. I could not identify or correct for any errors in self-reporting this data and all data was included in the study.

As mentioned in Chapter 1, faculty voluntarily select to be in the PP and commit to implementing the components of the Project. As a result, volunteer bias is introduced into the study and impacts reliability. Faculty participation in the PP was outside the scope of this project but it is a recommendation for future research in Chapter 5. While faculty participants commit to implementing all the components of the Project, outside of self-reporting in a faculty participant survey at the end of the semester, there is no guarantee that they implement all of the activities successfully (e.g., conduct a 1:1 meeting with *every single* student in the PP class).

CHAPTER SUMMARY

While an abundance of literature confirms that student-faculty interactions positively influence student retention, few studies look at the impact of intentional student-faculty interactions on student retention. Studies that do look at student-faculty interactions tend to focus on the quantity of student-faculty interactions as measured by office hour visits or informal interactions, and many studies use qualitative data to inform the impact of these interactions on student outcomes. This study measured the collective impact of the PP activities to increase student-faculty interactions using Propensity score analysis, a newer quantitative method for quasi-experimental studies.

PSA is endorsed by Astin and Antonio (2012) to study treatment effects in nonrandomized studies of program effectiveness. By using propensity score analysis, as compared to the more commonly used regression modeling to measure the effectiveness of a program, I decreased the sensitivity to data sparseness. The propensity score captures all the covariates into one measurement for comparison of treated and control groups (Benedetto et al., 2018; Porter, 2020). While logistic regression modelling assumes linearity between the covariates and the output, PSA assumes a nonlinear relationship (Benedetto et al., 2018; Porter, 2020). Astin's input-environment-outcome impact model also considers the relationship covariates (student inputs) have with the environment, thereby indirectly influencing the outcome. By controlling for the student inputs, I can better determine if the PP is influencing student retention. By determining the impact of the PP on student retention, the Project could be used by other institutions to enhance their social and academic environments to improve the retention for first-time in college, traditional-aged students making the transition to college.

CHAPTER 4: RESULTS

INTRODUCTION

This study evaluated if Oakton's PP, which creates intentional student-faculty interactions, influenced first-time in college, traditional-aged students within term and term-to-term retention. Using observational data sets from Oakton and an analytical approach to control for the confounding variables that introduce selection bias into a nonrandomized study, this study seeks to understand two underlying questions and associated hypotheses. Does participation in the PP influence term (fall) to term (spring) retention of first-time in college, traditional-aged students?

> $H1_0$: Participation in the Persistence Project does not significantly influence term-to-term retention of first-time in college, traditional-aged students.
>
> $H1_a$: Participation in the Persistence Project significantly influences term-to-term retention of first-time in college, traditional-aged students.

And, does participation in the Persistence Project influence year (fall) to year (fall) retention of first-time in college, traditional-aged students?

> $H2_0$: Participation in the Persistence Project does not significantly influence year to term retention of first-time in college, traditional-aged students.
>
> $H2_a$: Participation in the Persistence Project significantly influences year-to-year retention of first-time in college, traditional-aged students.

This chapter provides the detailed results which are organized by descriptive statistics and research questions and hypotheses. Statistical results are organized into data sets by descriptive and inferential statistical results. Descriptive statistics are organized into three data sets. The results for each study cohort, fall 2018 and fall 2019, are discussed separately. The COVID pandemic disrupted teaching and learning at Oakton in March 2020 impacting the fall 2019 study cohort. I wanted to look at this data independent of the fall 2018 study cohort. However, the research questions addressed fall-to-spring and fall-to-fall retention of students regardless of the cohort and the recommendations in Chapter 5 are based on the collective results of the study.

DESCRIPTIVE STATISTICS

Descriptive statistics are provided for each cohort and are organized into two sections, cohort descriptives and descriptives of the probability of treatment assignment. The first data table describes the means, standard deviations and numbers (*N*) for each covariate (independent variable) and the percentage and number (*N*) for each dependent variable (outcome) prior to propensity score determination for each cohort. The second and third data tables describe the means, standard deviations, and number for each cohort based on PP participation (treated or untreated) by cohort.

Descriptives by Cohort

Table 2 provides the descriptive statistics of independent variables and retention rates (dependent variables) for first-time in-college, traditional-aged students that enrolled in Oakton in fall 2018 and fall 2019 and were included in the study. Table 2 is organized by descriptives for each covariate, including mean, standard deviation and number (*N*) (see Table 2). Originally, I proposed two additional covariates not listed in Table 3. Students who identified as Native American/Alaskan Native were not included in the final analysis. During logit modeling to predict PP participation probabilities, STATA dropped this covariate because it is not possible to create data for such a small sample. As a result, three students in the fall 2018 cohort and two students in the fall 2019 cohort were removed from the study and the covariate was not included in the propensity score analysis. One other covariate and the associated subjects were removed from the analysis. A binary variable was created for missing GPA data. STATA omitted the missing GPA data covariate during logit modeling because of collinearity. This resulted in the removal of 151 students from the fall 2018 cohort and 127 students from the fall 2019 cohort. The final number of students in the study was 991 in the fall 2018 cohort and 1,047 in the fall 2019 cohort. The descriptive data between the two cohorts is consistent and there are not any large variations in any one variable between the two cohorts.

The fall 2018 cohort had higher fall-to-spring and fall-to-fall retention means than the fall 2019 cohort while numbers (N) were similar between the two cohorts. The fall 2018 cohort had a fall-to-spring retention mean of .802 while the fall 2019 cohort fall-to-spring retention mean was .783 (see Table 2). The fall-to-fall retention rates decreased for both cohorts and the difference between the cohorts' fall-to-fall retention means was larger. The mean fall-to-fall retention for the 2018 cohort was .646 while the fall-to-fall retention mean for the 2019 cohort was .597 (see Table 2). The COVID pandemic impacted teaching in learning in spring 2020 and may explain the difference in retention rates between the two cohorts. The impact of COVID-19 on the retention rates of students in higher education is discussed later in this chapter.

Table 2. Descriptive Statistics of First-Time In-College, Traditional-Aged Oakton Study Participants Independent Variables by Cohort, Fall 2018 and Fall 2019

Variables	Cohort	Mean	SD	N
Independent Variables				
First-generation	Fall 2018	.367	.482	419
	Fall 2019	.385	.487	452
Not first-generation	Fall 2018	.350	.477	226
	Fall 2019	.358	.480	252
Unknown first-generation status	Fall 2018	.435	.496	497
	Fall 2019	.400	.490	470
Female	Fall 2018	.422	.496	482
	Fall 2019	.429	.495	504
Male	Fall 2018	.578	.494	660
	Fall 2019	.571	.495	670
Pell-awarded	Fall 2018	.370	.483	423
	Fall 2019	.353	.478	414
Not Pell-awarded	Fall 2018	.630	.483	719
	Fall 2019	.647	.478	760
Asian/Pacific Islander	Fall 2018	.247	.431	282
	Fall 2019	.249	.432	292
Black, non-Hispanic	Fall 2018	.070	.255	80
	Fall 2019	.083	.275	97
Hispanic	Fall 2018	.220	.414	251
	Fall 2019	.211	.409	248
White, non-Hispanic	Fall 2018	.415	.493	474
	Fall 2019	.415	.493	487
Unknown race/ethnicity	Fall 2018	.048	.214	55
	Fall 2019	.043	.202	50
High school GPA, weighted, at or above 3.0	Fall 2018	.309	.462	306
	Fall 2019	.332	.471	348
High school GPA, weighted, below 3.0	Fall 2018	.691	.462	685
	Fall 2019	.668	.471	699
Developmental/ESL English placement	Fall 2018	.344	.475	393
	Fall 2019	.354	.479	416
College level English placement	Fall 2018	.656	.475	749

VARIABLES	COHORT	MEAN	SD	N
	Fall 2019	.646	.479	758
Full-time enrollment status	Fall 2018	.577	.495	654
	Fall 2019	.544	.498	639
Part-time enrollment status	Fall 2018	.427	.495	488
	Fall 2019	.456	.498	535
No educational plan	Fall 2018	.513	.500	586
	Fall 2019	.479	.500	562
Educational plan	Fall 2018	.487	.500	556
	Fall 2019	.521	.500	612
Certificate-seeking	Fall 2018	.119	.324	136
	Fall 2019	.106	.309	125
Degree-seeking	Fall 2018	.881	.324	1006
	Fall 2019	.894	.309	1049
College-level math placement	Fall 2018	.296	.457	338
	Fall 2019	.313	.464	368
Developmental math placement	Fall 2018	.704	.457	804
	Fall 2019	.687	.464	806
Standardized test scores SAT below 1070	Fall 2018	.501	.500	572
	Fall 2019	.574	.495	674
Standardized test scores SAT at or above 1070	Fall 2018	.499	.500	570
	Fall 2019	.426	.495	500
Dependent Variables				
Fall-to-spring retention	Fall 2018	.802	.399	916
	Fall 2019	.783	.413	919
Fall-to-fall retention	Fall 2018	.646	.478	738
	Fall 2019	.597	.143	701

Note: N = 2,316 (1,142 in the fall 2018 cohort and 1,174 in the fall 2019 cohort)

The overall fall 2018 and fall 2019 cohort data was also disaggregated by those students who participated in the PP (treated) and those who did not participate in the Project (untreated) (Table 3). Percent participation and numbers (*N*) were similar to a between the two cohorts.

Table 3. Project Participation of First-Time In-College, Traditional-Aged Oakton Study Participants by Cohort, Fall 2018 and Fall 2019

VARIABLES	COHORT	%	N
Participated in Persistence Project	Fall 2018	39.0	445
	Fall 2019	41.0	475
Did not participate in Persistence Project	Fall 2018	61.0	697
	Fall 2019	59.5	699

Note. N = 2,316 (1,142 in the fall 2018 cohort and 1,174 in the fall 2019 cohort)

Table 4 is organized by covariates for treated and untreated groups and includes mean, standard deviation, and *N* for each covariate for the fall 2018 cohort and reflects removal of the missing GPA and the Native American/Alaskan Native covariates (see Table 4). Variation in covariate distribution is more evident between treated and untreated groups as compared to the aggregated cohort data. Covariates that were related to high school GPA, enrollment status, educational plans, and standardized test scores were the most different between treated and untreated groups.

Table 5 includes the % and *N* for the retention outcomes for the fall 2018 cohort. The fall 2018 treated group had higher fall-to-spring retention, 86%, as compared to those subjects in the untreated group, 77%. The fall-to-fall retention rates for the treated group was also higher than the untreated group. Students in the project persisted to the following fall term at higher rates, 71% as compared to the nonparticipants, 61%. The increased fall-to-spring and fall-to-fall retention rates for the fall 2018 cohort parallels the consistent increase in retention for PP participants since the inception of the Project.

Table 6 captures the descriptive statistics for first-time in-college, traditional-aged students that enrolled in Oakton in fall 2019 and were included in the study. Table 6 is organized by covariates treated and untreated groups and includes means, standard deviations, and number (*N*) for each covariate and reflects removal of the missing GPA and the Native American/Alaskan Native covariates (Table 6). Like cohort 2018, the fall 2019 cohort data disaggregated by treated and untreated shows greater variation in covariate means than was evident when comparing the aggregated fall 2018 and fall 2019 cohorts. In the fall 2019 comparison of covariates by treated and untreated groups, larger mean differences were noted for first-generation status, Asian and Pacific Islander race/ethnicity, high school GPA, English/ESL and math placements, educational plans, enrollment status, standardized test scores, and academic goal.

Table 4. Descriptive Statistics of Independent Variables of Study Subjects by Treatment Group, Fall 2018 Cohort

VARIABLES	SAMPLE	MEAN	*SD*	*N*
Independent Variables				
First-generation	Treated	.346	.476	154
	Untreated	.380	.486	265
Not first-generation	Treated	.377	.485	93
	Untreated	.334	.472	133
Unknown first-generation	Treated	.445	.498	198
	Untreated	.429	.495	299
Female	Treated	.436	.496	194
	Untreated	.413	.493	288
Male	Treated	.564	.496	251
	Untreated	.587	.493	409
Pell-awarded	Treated	.393	.489	175
	Untreated	.356	.479	248
Not Pell-awarded	Treated	.607	.489	270

Variables	Sample	Mean	*SD*	*N*
	Untreated	.644	.479	449
Asian/Pacific Islander	Treated	.261	.439	116
	Untreated	.238	.426	166
Black, non-Hispanic	Treated	.061	.239	27
	Untreated	.076	.265	53
Hispanic	Treated	.202	.402	90
	Untreated	.231	.422	161
White, non-Hispanic	Treated	.422	.496	188
	Untreated	.410	.492	286
Unknown race/ethnicity	Treated	.054	.226	24
	Untreated	.044	.206	31
High school GPA, weighted, at or above 3.0	Treated	.369	.483	142
	Untreated	.271	.445	164
High school GPA, weighted, below 3.0	Treated	.631	.483	243
	Untreated	.729	.445	442
Developmental/ESL English placement	Treated	.357	.480	159
	Untreated	.336	.473	234
College level English placement	Treated	.643	.480	286
	Untreated	.664	.473	463
Full-time enrollment status	Treated	.688	.464	306
	Untreated	.499	.500	348
Part-time enrollment status	Treated	.312	.464	139
	Untreated	.500	.500	349
No educational plan	Treated	.456	.499	203
	Untreated	.549	.498	383
Educational plan	Treated	.544	.499	242
	Untreated	.451	.498	314
Certificate-seeking	Treated	.130	.337	58
	Untreated	.112	.315	78
Degree-seeking	Treated	.870	.337	387
	Untreated	.888	.315	619
College-level math placement	Treated	.306	.461	136
	Untreated	.290	.454	202
Developmental math placement	Treated	.694	.461	309

Variables	Sample	Mean	*SD*	*N*
	Untreated	.710	.454	495
Standardized test scores SAT below 1070	Treated	.533	.499	237
	Untreated	.480	.500	335
Standardized test scores SAT at or above 1070	Treated	.467	.499	208
	Untreated	.513	.500	362

Note. N = 1,142 (445 in the PP and 697 not in the PP)

Table 5. Retention Rates of Study Subjects by Treatment Group, Fall 2018 Cohort

Outcome Variables	Sample	%	N
Fall-to-spring retention	Treated	86%	445
	Untreated	77%	697
Fall-to-fall retention	Treated	71%	445
	Untreated	61%	697

Note. N = 1,142 (445 in the PP and 697 not in the PP)

Table 6. Descriptive Statistics of Independent Variables of Study Subjects by Treatment Group, Fall 2019 Cohort

Variables	Sample	Mean	SD	N
Independent Variables				
First-generation	Treated	.402	.491	191
	Untreated	.373	.484	261
Not first-generation	Treated	.332	.472	95
	Untreated	.376	.485	15
Unknown first-generation	Treated	.398	.490	281
	Untreated	.402	.491	189
Female	Treated	.434	.496	206
	Untreated	.426	.495	298
Male	Treated	.566	.496	269
	Untreated	.574	.495	401
Pell-awarded	Treated	.366	.482	174
	Untreated	.343	.475	240

Variables	Sample	Mean	SD	N
Not Pell-awarded	Treated	.634	.482	301
	Untreated	.657	.475	459
Asian/Pacific Islander	Treated	.272	.445	129
	Untreated	.233	.423	163
Black, non-Hispanic	Treated	.074	.262	35
	Untreated	.089	.285	62
Hispanic	Treated	.208	.407	99
	Untreated	.213	.410	149
White, non-Hispanic	Treated	.398	.490	189
	Untreated	.426	.495	298
Unknown race/ethnicity	Treated	.048	.215	23
	Untreated	.039	.193	27
High school GPA, weighted, at or above 3.0	Treated	.367	.483	158
	Untreated	.308	.462	190
High school GPA, weighted, below 3.0	Treated	.633	.482	273
	Untreated	.692	.462	426
Developmental/ESL English placement	Treated	.309	.463	147
	Untreated	.385	.487	269
College level English placement	Treated	.691	.463	328
	Untreated	.615	.487	430
Full-time enrollment status	Treated	.703	.457	334
	Untreated	.436	.496	305
Part-time enrollment status	Treated	.297	.457	141
	Untreated	.564	.496	394
No educational plan	Treated	.389	.488	185
	Untreated	.539	.499	377
Educational plan	Treated	.611	.489	290
	Untreated	.461	.499	322
Certificate-seeking	Treated	.084	.278	40
	Untreated	.122	.327	85
Degree-seeking	Treated	.916	.278	435
	Untreated	.878	.327	614
College-level math placement	Treated	.345	.476	164
	Untreated	.282	.455	204

Variables	Sample	Mean	SD	N
Developmental math placement	Treated	.655	.476	311
	Untreated	.708	.455	495
Standardized test scores SAT below 1070	Treated	.604	.490	287
	Untreated	.554	.497	387
Standardized test scores SAT at or above 1070	Treated	.654	.476	188
	Untreated	.446	.497	312

Note. N = 1,174 (475 in the PP and 699 not in the PP)

As seen in the Fall 2018 cohort outcome descriptive data, the fall 2019 treatment group also had increased fall-to-spring retention, 86%, as compared to the untreated subjects, 73% (Table 7). Students in the PP continued to persist to the next fall at higher rates than the untreated group, 67% and 55%, respectively (see Table 8). The fall 2019 cohort continued to demonstrate the increased retention of PP participants as compared to nonparticipants that Oakton had been witnessing since the Project was first piloted in 2016.

Table 7. Retention Rates of Study Subjects by Treatment Group, Fall 2019 Cohort

Outcome Variables	Sample	%	N
Fall-to-spring retention	Treated	86%	475
	Untreated	73%	699
Fall-to-fall retention	Treated	67%	475
	Untreated	55%	699

Note. N = 1,174 (475 in the PP and 699 not in the PP)

Reporting the disaggregated data for each cohort revealed differences between the two cohorts, including differences in covariate means between treated and untreated groups and in the outcomes. Covariate differences between the two cohorts were evident in the percent of students who were in the treated or untreated group for a particular covariate and the difference in percentages between treated and treated groups. For instance, in the fall 2019 cohort there was a higher percentage of students who identify as first generation in PP classes (40%) as compared to the fall 2018 cohort (35%), yet the percentage of subjects in the untreated group was similar between the 2018 and 2019 cohorts, 38% and 37% respectively.

The percentage of students who placed into developmental English or ESL classes was different between cohorts for both treated and untreated groups. In the fall 2018 cohort, 36% of students who placed into developmental English/ESL were in a PP class as compared to 34% of that were not in a PP class (see Table 4). For the 2019 cohort, 31% of students who placed into developmental English/ESL were in a PP class as compared to 39% of students who did not enroll in a PP class. Another example of a difference between the two cohorts is seen with the certificate-seeking covariate. The fall 2018 cohort had more certificate seeking students in a PP class (11%) as compared to the fall 2019 cohort (9%). The percentage of certificate-seeking students in the treatment and untreated groups was similar for the fall 2018 cohort (see Table 5), while the fall 2019 cohort saw a lower percentage of certificate-seeking students in a PP class (9%) as compared to the untreated group (12%) (see Table 6).

While the treated subjects in both cohorts had higher within-year and year-to-year retention as the untreated subjects, as seen in Table 8, the year-to-year retention rates for the fall 2019 cohort were lower for both the treated (67%) and untreated (55%) as compared to the fall 2018 cohort (treated = 71%, untreated = 61%). And the fall-to-spring retention for the fall 2019 untreated group was lower (73%) than the fall 2018 untreated group (77%). The fall-to-spring retention rates were the same for the fall 2018 and fall 2019 treated groups, 86% (see Table 8). The COVID pandemic may explain the difference between the cohort fall-to-fall retention rates. The pandemic impacted Oakton in March 2020 and the college shifted to remote learning for the second half of the spring 2020 semester. Students were given the opportunity to withdraw from classes without financial penalty in Spring 2020 and all classes were offered online through the fall 2020 semester. Nationally, fall 2019 to fall 2020 enrollment dropped by 7.5% (Illinois Community College Board [ICCB], 2020) and fall-to-fall retention decreased 4.9% (Howell et al., 2021). Illinois community colleges saw a 13.7% decrease in headcount. Oakton's fall 2019 to fall 2020 enrollment decreased 12.4%. In comparison, Illinois community colleges experienced a 4.2% decline from fall 2018 to fall 2019 and Oakton's fall 2018 to fall 2019 enrollment decreased 4.4% (ICCB, 2019).

Table 8. Retention Rates for Treated and Untreated by Cohort

COHORT	RETENTION TERMS	TREATED %	UNTREATED %
Fall 2018	Fall 2018 to Spring 2019	86	77
	Fall 2018 to Fall 2019	71	61
Fall 2019	Fall 2019 to Spring 2020	86	73
	Fall 2019 to Fall 2020	67	55

Note. Fall 2018, N = 1,142 (445 in the PP and 697 not in the PP); Fall 2019, *N* = 1,174 (475 in the PP and 699 not in the PP)

Descriptives of Probability of Treatment Assignment

Tables 9 and 10 represent the data from the logistic regression for the fall 2018 and fall 2019 cohorts, respectively. The logit tables include variables that predict the probability and odds of treatment assignment, in this case assignment to the PP. Based on observed baseline characteristics, they are used to determine the propensity scores in preparation for matching. The tables include the coefficients (C), standard errors, odds ratios (OR), the 95% confidence intervals (CI) for the odds ratios, and *p* values for each covariate that have been identified as predictors of student retention.

In the fall 2018 cohort, three variables are statistically significant in the model, high school GPA below 3.0 ($p < .01$), part-time enrollment status ($p < .001$), and standardized test scores below 1070 ($p < .01$) (see Table 9). A high school GPA of less than 3.0, and part-time enrollment status are negatively associated with participation in the PP, while the covariate of an SAT score below 1070 is positively associated with participation in the PP (see Table 9). The coefficients and odds ratio for part-time enrollment status (C =-.720, OR =.487, 95% CI: .364, .651) and high school GPA below 3.0 (C = -.419, OR = .657, 95% CI: .482, .897) indicate that part-time students and students with a high school GPA below 3.0 have a lower probability or lower odds of participating in a PP class than the reference subjects, full-time enrollment status and high school GPA equal to or greater than 3.0, respectively. Interestingly, the coefficient and odds ratio for students with a standardized exam score below 1070 (C = .365, OR = 1.44, 95% CI: 1.08, 1.92) had a higher probability or odds of being in a PP class as compared to students with an SAT score equal or greater than 1070.

In the fall 2019 cohort, part-time enrollment status ($p <. 001$), no educational plans ($p < .01$), and standardized test scores below 1070 ($p < .05$) were significant for predicted participation in the PP (see Table 10). Like the fall 2018 cohort, part-time enrollment status is negatively associated with participation in the PP, while an SAT score below 1070 is positively associated with participation in this PP. The coefficient and odds ratio for subjects enrolled part-time in fall 2019 (C = -1.06, OR = .347, 95% CI: .261, .460) indicate a decreased probability or odds that these subjects will be in a PP class as compared to students who enroll full-time. A lack of an educational plan was negatively associated with participation in the PP (see Table 10). The coefficient and odds ratio for subjects who did not have an educational plan (C = -.444, OR

= .641, 95% CI: .491, .839) indicate that these students have a decreased probability or odds of enrolling in a PP class as compared to students who had an educational plan. And, similar to the fall 2018 cohort, students who had standardized exam scores below 1070 has an increased probability (C = .289, OR = 1.33, 95% CI: 1.00, 1.78) of enrolling in a PP class than students with standardized exams scores at or above 1070.

Table 9. Logit Predicting Probability of Treatment Assignment, Fall 2018 Cohort

Covariate	Coefficient	SE	Odds Ratio	SE	[95% Confidence Interval]		P < |z|
First-generation	-.122	.142	.885	.126	.669751	1.169256	0.390
Female	.051	.139	1.05	.146	.8016106	1.380451	0.715
Pell-Awarded	.036	.145	1.04	.150	.7810474	1.377236	0.801
Asian/Pacific Islander	-.036	.177	.890	.158	.6292946	1.259315	0.511
Black, non-Hispanic	-.125	.275	.882	.242	.5150946	1.511318	0.648
Hispanic	-.116	.180	.890	.160	.6255793	1.267596	0.520
Unknown race/ethnicity	.211	.336	1.23	.415	.6393036	2.385087	0.530
High school GPA, weighted, below 3.0	-.419**	.159	.657**	.104	.4818235	.8971313	0.008
Developmental/ESL English placement	.177	.159	1.19	.190	.874787	1.63031	0.264
Part-time enrollment status	-.720***	.148	.487***	.072	.3642317	.6505051	0.000
No educational plan	-.145	.137	.865	.119	.6607799	1.132217	0.291
Certificate-seeking	.163	.209	1.18	.246	.7814238	1.772354	0.436
Developmental math placement	-.021	.164	.979	.161	.7091945	1.350929	0.896
Standardized test scores SAT below 1070	.365*	.147	1.44*	.212	1.080534	1.921188	0.013
_cons	-.028	.191	.973	.186	.6683752	1.415451	0.885

Note: *N*=1,047
p<.05. ***p*<.01. ****p*<.001.

Table 10. Logit Predicting Probability of Treatment Assignment for Fall 2019 Cohort

Covariate	Coefficient	SE	Odds Ratio	SE	[95% Confidence Interval]		P < |z|
First-generation	.124	.139	1.13	.158	.8614648	1.488181	0.373
Female	.056	.141	1.06	.149	.8022722	1.394211	0.691
Pell-Awarded	-.138	.148	.871	.129	.65203	1.163327	0.349
Asian/Pacific Islander	-.023	.176	.978	.172	.6930588	1.379145	0.898
Black, non-Hispanic	-.244	.261	.976	.255	.5846207	1.628918	0.926
Hispanic	.170	.178	1.11	.211	.836178	1.680267	0.340
Unknown race/ethnicity	.495	.345	1.64	.211	.836178	1.680267	0.152
High school GPA, weighted, below 3.0	.087	.155	1.09	.169	.8051435	1.479037	0.573
Developmental/ESL English placement	-.298	.157	.742	.117	.5453482	1.010891	0.059
Part-time enrollment status	-1.06***	.144	.347***	.050	.2612126	.4597485	0.000
No educational plan	-.444**	.137	.641**	.088	.4905921	.838548	0.001
Certificate-seeking	-.125	.280	.882	.201	.5644395	1.379644	0.583
Developmental math placement	-.132	.156	.876	.137	.6453835	1.18884	0.395
Standardized test scores SAT below 1070	.289*	.147	1.33*	.196	1.001199	1.778902	0.049
_cons	.158	.185	1.17	.217	.8148712	1.684673	0.393

Note. $N = 1{,}047$.

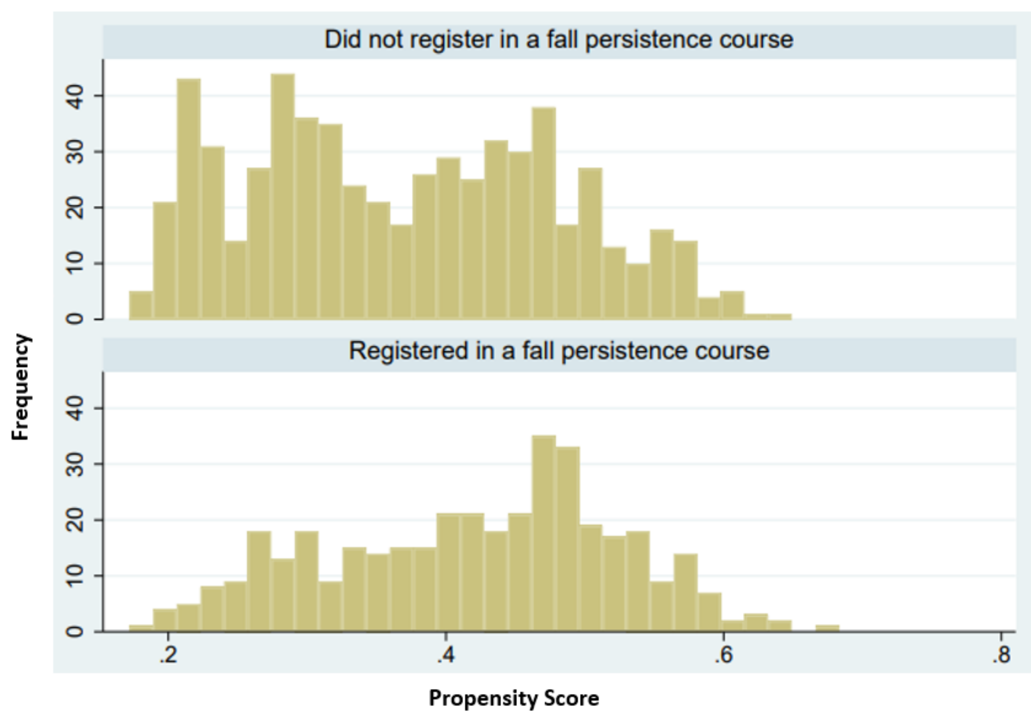
$p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Evaluating Propensity Score and Covariate Balance Before Matching

The coefficients from the logit tables (see Tables 9 and 10) and the student characteristics were used to predict probability of being in the PP for each student. This predicted probability is captured in a single value, the propensity score. The characteristics of each student and associated coefficient value results in each student having their own propensity score. After propensity scores were created, common support was assessed via histograms and identifying minimum and maximum propensity score values. Histograms are a graphical diagnostic that provides a way to evaluate covariate balance. Figures 2 and 3 illustrate the propensity score distribution and frequency for treated and untreated groups for each cohort model. Each figure includes two histograms of propensity score distribution, one for those that participated in a PP class (treated) and one for those who did not participate in the PP (untreated). Figure 2 displays the range and distribution of propensity scores for the fall 2018 cohort and Figure 3 depicts the distribution of propensity scores between the untreated and treated groups for the fall 2019 cohort.

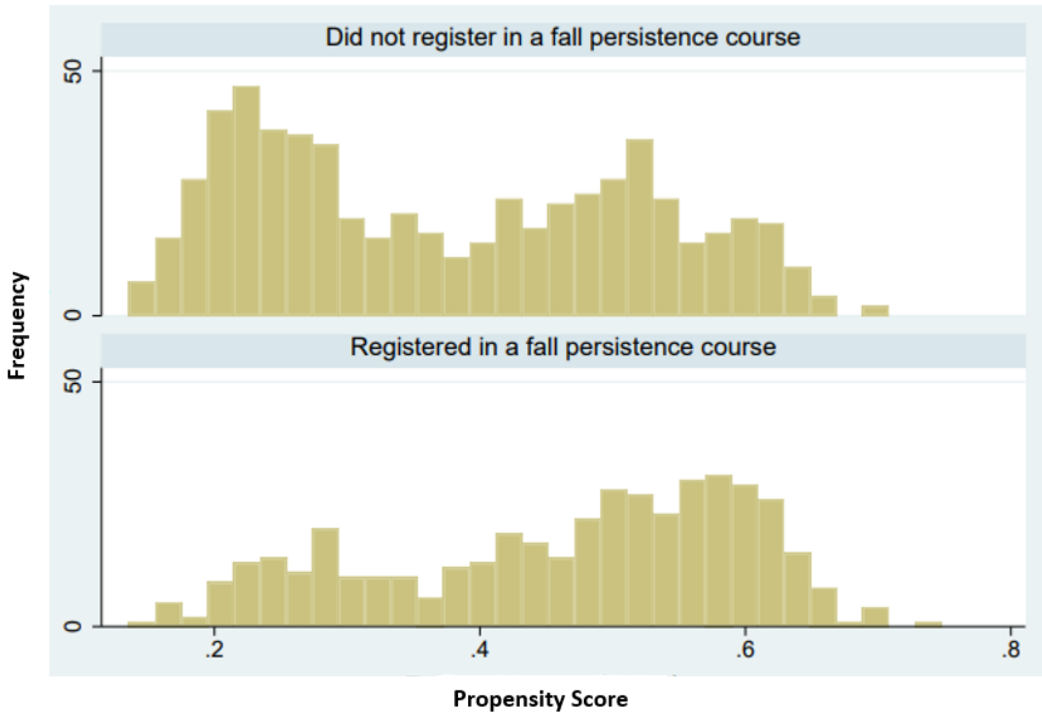
Propensity score overlap of the distribution of covariates across treated and untreated groups within the area of comment support was observed for each cohort. There is general overlap in the distribution of propensity scores between the treatment and control groups for each cohort (see Figures 2 and 3). The frequency of each propensity score is not as consistent between each group. The lower propensity scores are in higher frequency for the untreated group than the treated group. However, when assessing balance of propensity scores as an indicator of covariate balance, distribution is the critical factor. The higher frequency in the untreated group within lower propensity score bins indicates there are more individuals in these bins in the untreated group that can be used for the nearest neighbor (NN) with replacement matching method. The second way in which covariate balance across groups was achieved through comparisons of minima and maxima propensity score values and removal of cases that fall outside of the bounds of comment support. Propensity scores below the minimum and above the maximum propensity scores for the opposite treatment category were removed from the study sample to create an area of common support an accepted method in propensity score analysis (Caliendo & Kopeinig, 2008). For the fall 2018 cohort, propensity scores outside of [.1803152, .6488762] were removed, resulting in the removal of 152 observations below the minimum and two observations above the maximum. For the fall 2019 cohort, propensity scores outside of [.1386539, .7017123] were removed, resulting is the removal of 128 observations below the minimum and one observation above the maximum.

Figure 2. Fall 2018 Cohort Propensity Score Distribution Before Matching.



Note. This histogram demonstrates graphical common support as indicated by the overlap in the distribution of propensity scores for subjects in the treated group (registered in a fall persistence course) and in the untreated group (did not register in a fall persistence course) for the fall 2018 cohort. The histogram also demonstrates the frequency of propensity scores within each bin of propensity score distribution.

Figure 2. Fall 2019 Cohort Propensity Score Distribution Before Matching.



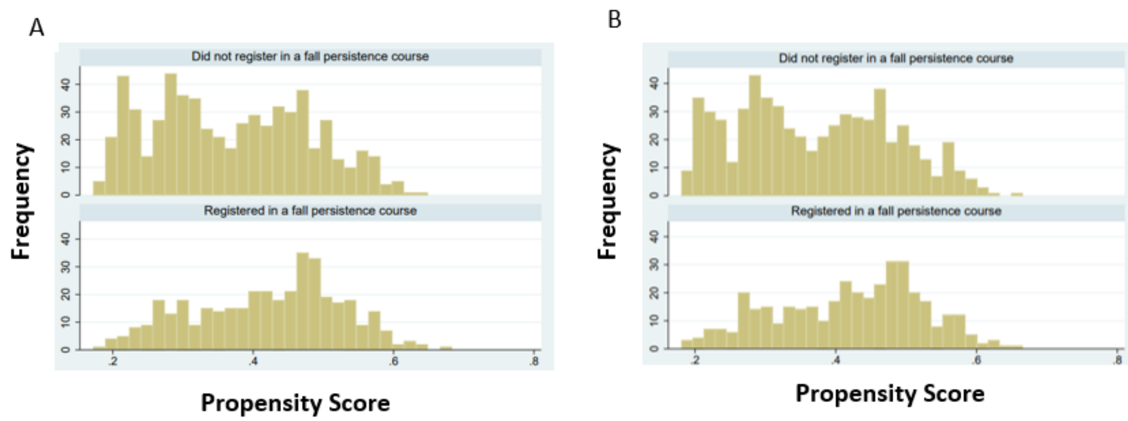
Note. This histogram demonstrates graphical common support as indicated by the overlap in the distribution of propensity scores for subjects in the treated group (registered in a fall persistence course) and in the untreated group (did not register in a fall persistence course) for the fall 2019 cohort. The histogram also demonstrates the frequency of propensity scores within each bin of propensity score distribution.

Evaluating Propensity Score and Covariate Balance After Matching

After common support was established, NN with replacement and a caliper were used to identify at least one match from the control group for each subject in the treatment group. This provided an opportunity to check for balance in covariates across matched treated and control groups. Common support was reassessed after matching for each cohort visually and by using the minima and maxima comparisons identified pre-match. For each cohort only one subject had a propensity score that did not align with those in common support and these subjects were removed from the analyses. This indicates similarities in propensity scores between matched treated and control groups that matches between groups was good (Tumlinson et al., 2014).

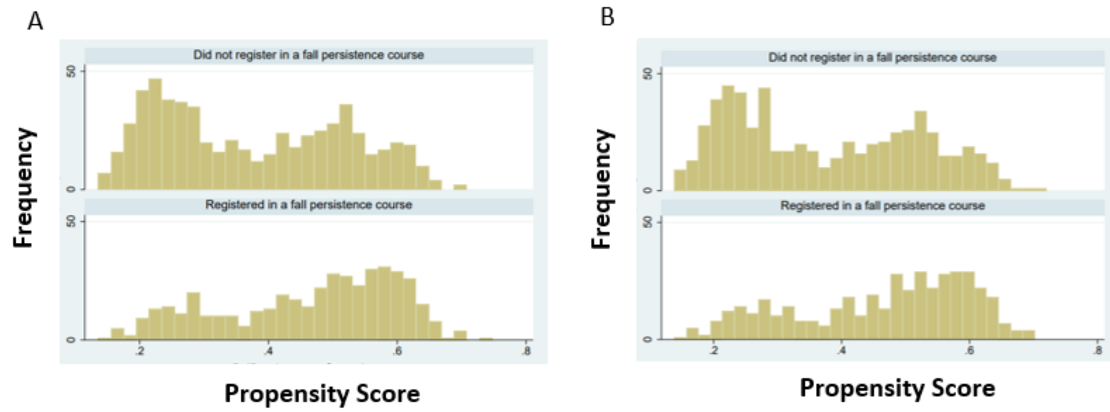
Histograms were created after establishing common support via minima and maxima comparison and after matching to assess continued propensity score distribution overlap. Figures 4 and 5 show a comparison of propensity score distribution before and after common support and matching and demonstrate the continued overlap in the distribution of propensity scores for those in a PP class (treated) and for those participants not in a PP class (control) for both cohorts. There were some minor changes in the frequency of propensity scores.

Figure 3. Fall 2018 Cohort Propensity Score Distribution Before and After Matching.



Note. This histogram demonstrates the distribution of propensity scores for subjects in the treated group (registered in a fall persistence course) and in the control group (did not register in a fall persistence course) for the fall 2018 cohort before and after matching. Panel A: Distribution of propensity score before establishing common support and matching. Panel B: Distribution of propensity scores after establishing common support and matching. The histogram also demonstrates the frequency of propensity scores within each bin of propensity score distribution.

Figure 4. Fall 2019 Cohort Propensity Score Distribution Before and After Matching.



Note. This histogram demonstrates the distribution of propensity scores for subjects in the treated group (registered in a fall persistence course) and in the control group (did not register in a fall persistence course) for the fall 2019 cohort before and after matching. Panel A: Distribution of propensity score before established common support and matching. Panel B: Distribution of propensity scores after establishing common support and matching. The histogram also demonstrates the frequency of propensity scores within each bin of propensity score distribution.

Two additional methods were used to evaluate covariate balance between matched treated and control groups. Standardized difference of means between the matched treated and control groups and % bias reduction were examined to identify any imbalances. The means, percent bias, percent reduction in bias, and *t*-test results for each cohort after matching by covariates are noted in Tables 7 and 8. Propensity score analysis (PSA) is used to reduce selection bias that is inherent in nonrandomized studies of observational data by creating a single value from the set of covariates identified in this study. This value is the propensity score and it determines the probability an individual will be assigned to the treatment group. It is important to note the % bias and the % reduction in bias since that is the primary goal when using PSA – to achieve as near perfect balance as possible to make a causal inference in a nonrandomized study. *T*-test values and an evaluation of standardized difference means were used to compare treated and control groups before and after matching to determine any significant differences between the baseline covariates.

Table 11 identifies the means and percent bias for treated and control groups before and after matching for the fall 2018 cohort. A percent bias of less than 10% between the matched treated and control groups suggests balanced covariates between groups. In this study bias was not reduced and increased for several covariates that had smaller numbers (*N*), such as Black, ESL/EGL placement, and certificate seeking (Table 11) which may result in less balance between treated and control groups. If the percent bias is above 10%, the percent reduction of bias and *t*-test results can be reviewed to determine if reduction is sufficient and if there is a significance between the matched treated and control groups. For the fall 2018 cohort, the majority of the covariate percent bias was below 10%. The only covariate that had a percent bias above 10% after matching was certificate-seeking students (11.7%). However, there wasn't a significant difference between the matched treated and control groups as indicated by the *p* value ($p < .05$) (see Table 11). There were statistical differences noted in the unmatched sample between treated and control groups for the high school GPA ($p < .01$), part-time enrollment status ($p < .001$), no educational plan ($p < .05$), and standardized test score ($p < .05$) covariates that were adjusted after matching. However, *t*-test significance is not recommended to evaluate covariate balance after matching because *t* tests are sensitive to sample size. As sample size decreases, which may occur after matching, the *p* value may be inflated.

Table 11. Descriptive Statistics of Matched Groups after Propensity Score Matching, Fall 2018 Cohort

Independent Variables	Sample	Means		Bias		T-test	
		Treated	Control	%	% Reduction	T	P > |T|
First-generation	Unmatched	.354	.389	-7.2		-1.10	0.270
	Matched	.352	.349	0.8	88.8	0.11	0.910
Female	Unmatched	.438	-.419	3.8		0.58	0.564
	Matched	.439	.435	0.8	79.0	0.11	0.913
Pell awarded	Unmatched	.396	.368	5.8		0.89	0.372
	Matched	.394	.355	8.1	-38.5	1.12	0.263
Asian/Pacific Islander	Unmatched	.237	.224	3.2		0.49	0.624
	Matched	.235	.258	-5.6	-74.5	-0.75	0.451
Black, non-Hispanic	Unmatched	.073	.073	-1.0		-0.15	0.881
	Matched	.071	.046	9.6	-878.4	1.47	0.143
Hispanic	Unmatched	.219	.247	-6.6		-1.01	0.314
	Matched	.219	.230	-2.5	62.6	-0.35	0.729
Unknown race/ethnicity	Unmatched	.047	.040	3.5		0.54	0.588
	Matched	.047	.042	2.6	26.9	0.35	0.726
High school GPA, weighted, below 3.0	Unmatched	.633	.728	-20.6		-3.19	0.001
	Matched	.632	.620	2.5	87.7	0.34	0.737
Developmental/ESL English placement	Unmatched	.315	.313	0.5		0.07	0.942
	Matched	.316	.292	5.1	-972.9	0.71	0.480
Part-time enrollment status	Unmatched	.286	.470	-38.5		-5.84	0.000
	Matched	.285	.260	5.2	86.5	0.77	0.441
No educational plan	Unmatched	.448	.526	-15.8		-2.41	0.016
	Matched	.446	.448	-0.3	98.3	-0.04	0.971
Certificate-seeking	Unmatched	.125	.114	3.3		0.51	0.610
	Matched	.125	.087	11.7	-251.8	1.70	0.090
Developmental math placement	Unmatched	.682	.692	-2.1		-0.32	0.747
	Matched	.684	.638	9.8	-368.1	1.34	0.182
Standardized test scores SAT below 1070	Unmatched	.594	.523	14.2		2.18	0.030
	Matched	.595	.568	5.5	61.2	0.77	0.443

Note. Matched *N* = 604; Unmatched *N* = 383
p < .05. ***p* < .01. ****p* < .001

The fall 2019 means and percent bias for treated and control groups before and after matching indicates covariate balance between the matched treated and control groups (Table 12). The percent bias between matched treated and control groups was below 10% for each covariate. While none of the *t* tests revealed a significance of $p < .05$ between the matched treated and control groups, *t* tests are not the best test to analyze covariate balance after matching since *t* tests are sensitive to sample size. There were significant differences noted in the unmatched sample between treated and control groups for developmental EGL/ESL placement ($p < .05$), part-time enrollment status ($p < .001$), no educational plan ($p < .001$), and certificate seeking ($p < .05$) covariates that were adjusted after matching.

Because *t* tests are sensitive to sample size, the standardized difference in means was used to do another balance check and is a highly recommended alternative to *t*-test values (Austin, 2009; Branson, 2021). I used standardized difference of means to conduct an additional balance test after matching. An imbalance between covariates may occur when standardized differences are greater than 0.2. For the fall 2018 cohort, the only covariate with a standardized difference of above 0.2 is part-time enrollment (.381) (Table 14). This may indicate a small effect size. A standardized difference of mean of 0.2 – 0.5 is considered a small effect size in that there is some difference between the means of the matched treated and control groups. However, as discussed in Chapter 3, there is not widely accepted criteria for determining imbalances.

Table 12. Descriptive Statistics of Matched Groups after Propensity Score Matching, Fall 2019 Cohort

Independent Variables	Sample	Means: Treated	Means: Control	Bias: %	Bias: % Reduction	T-Test: T	T-Test: P > |T|
First-generation	Unmatched	.402	.379	4.8		0.77	0.444
	Matched	.403	.379	5.0	-4.3	0.73	0.436
Female	Unmatched	-.437	.416	4.2		0.67	0.501
	Matched	.438	.400	7.8	-83.6	1.14	0.254
Pell awarded	Unmatched	.363	.348	3.1		0.49	0.622
	Matched	.361	.321	8.5	-175.2	1.26	0.208
Asian/Pacific Islander	Unmatched	.247	.223	5.6		0.89	0.372
	Matched	.247	.242	1.1	80.4	0.16	0.874
Black, non-Hispanic	Unmatched	.077	.085	-2.9		-0.45	0.650
	Matched	.077	.073	1.3	55.2	0.19	0.846
Hispanic	Unmatched	.219	.226	-1.8		-0.28	0.777
	Matched	.219	.212	1.7	5.6	0.52	0.804
Unknown race/ethnicity	Unmatched	.044	.034	5.2		0.83	0.406
	Matched	.044	.055	-5.4	-4.5	0.71	0.480
High school GPA, weighted, below 3.0	Unmatched	.635	.691	-11.9		-1.90	0.058
	Matched	.634	.627	1.5	87.6	0.21	0.832
Developmental/ESL English placement	Unmatched	.277	.367	-19.5		-3.08	0.002
	Matched	.275	.259	3.5	82.0	0.54	0.590
Part-time enrollment status	Unmatched	.279	.514	-55.3		-8.72	0.000
	Matched	.277	.275	0.5	99.1	0.08	0.939
No educational plan	Unmatched	.381	.527	-29.5		-4.68	0.000
	Matched	.380	.413	-6.9	76.8	-1.01	0.312
Certificate-seeking	Unmatched	.083	.122	-12.6		-1.98	0.048
	Matched	.084	.100	-4.6	63.4	-0.71	0.477
Developmental math placement	Unmatched	.644	.701	-12.1		-1.93	0.054
	Matched	.643	.642	0.2	97.9	0.04	0.972
Standardized test scores SAT below 1070	Unmatched	.649	.607	8.8		1.39	0.165
	Matched	.650	.670	-4.1	53.2	-0.61	0.541

Note. Matched $N = 604$; Unmatched $N = 383$
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 13. Standardized Difference of Means of Matched Treated and Control Groups, Fall 2018 Cohort

Independent Variables	Treated		Control		Standardized
	Mean	SD	Mean	SD	difference
First generation	.354	.479	.389	.488	0.072
Female	.438	.497	.419	.494	-0.038
Pell awarded	.396	.490	.368	.483	-0.058
Asian/Pacific Islander	.237	.426	.224	.417	-0.032
Black, non-Hispanic	.070	.256	.073	.260	0.010
Hispanic	.219	.414	.247	.431	0.066
Unknown race/ethnicity	.047	.212	.034	.200	-0.036
High school GPA below 3.0	.633	.483	.726	.445	0.028
Developmental EGL/ESL placement	.315	.465	.313	.464	-0.005
Part-time enrollment	.287	.453	.470	.500	0.381
No educational plan	.448	.498	.527	.500	0.157
Certificate seeking	.125	.331	.114	.318	-0.033
Developmental math placement	.682	.466	.692	.462	0.021
SAT below 1070	.594	.492	.523	.500	-0.142

Note. Assessing standardized differences between matched treated and control groups is another way to measure covariate balance. Standardized differences above 0.2 indicate a small effect size or differences between the matched treated and control groups for a covariate. Standardized differences above 0.5 indicate a medium effect size or imbalance. Standardized differences above 0.8 indicate a large effect size or imbalance.

The standardized difference of means for the fall 2019 cohort indicated relative balance across most covariates. The part-time enrollment status and no educational plan covariates had standardized means above the 0.20 difference that may indicate an imbalance (Table 14). The covariate no educational plan had a standardized mean difference of 0.294. This would indicate a small effect size or difference between the groups. The part-time enrollment had a standardized mean difference of 0.548 which is in the 0.5-0.8 mean difference range that is considered a moderate imbalance or medium effect size.

Table 14. Standardized Difference of Means of Matched Treated and Control Groups, Fall 2019 Cohort

Independent Variables	Treated Mean	Treated *SD*	Control Mean	Control *SD*	Standardized difference
First generation	.402	.491	.379	.486	-0.048
Female	.437	.497	.416	.493	-0.042
Pell awarded	.363	.481	.348	.477	-0.031
Asian/Pacific Islander	.247	.431	.223	.416	-0.056
Black, non-Hispanic	.077	.267	.085	.278	0.029
Hispanic	.219	.414	.226	.419	0.018
Unknown race/ethnicity	.044	.206	.034	.182	-0.055
High school GPA below 3.0	.635	.482	.691	.462	0.119
Developmental EGL/ESL placement	.277	.448	.368	.483	0.193
Part-time enrollment	.381	.486	.542	.499	0.548
No educational plan	.381	.486	.527	.500	0.294
Certificate seeking	.084	.277	.122	.323	0.121
Developmental math placement	.644	.479	.701	.458	0.121
SAT below 1070	.649	.478	.607	.489	-0.087

Note. Assessing standardized differences is another way to measure covariate balance between matched treated and control groups. Standardized differences above 0.2 indicate a small effect size or imbalance. Standardized differences above 0.5 a medium effect size or imbalance. Standardized differences above 0.8 indicate a large effect size or imbalance.

INFERENTIAL STATISTICS: HYPOTHESIS TESTING

Once propensity scores were estimated and treated and untreated study participants were matched and balanced, the average treatment effect was measured for each cohort by each outcome. The average treatment effect measured the average difference between the treated subjects observed outcome and their potential (counterfactual) outcome as captured by the matched control group. This section is organized by research question and associated hypotheses.

Research Question 1

Does participation in the Persistence Project influence term (fall) to term (spring) retention of first-time in college, traditional-aged students?

$H1_0$: Participation in the Persistence Project does not significantly influence term-to-term retention of first-time in college, traditional-aged students.

$H1_a$: Participation in the Persistence Project significantly influences term-to-term retention of first-time in college, traditional-aged students.

If first-time in-college, traditional-aged student participation in Oakton's Persistence Project influenced within-year retention, there would be a statistically significant difference between the matched treated and control groups on term-to-term retention. While the treatment effects are positive, they are not statistically significant (Table 15), indicating that participation in the project does not have a statistically significant influence on fall-to-spring retention after propensity score matching. Therefore, the null hypothesis cannot be rejected.

Table 15. Matching Estimates of Average Treatment Effects on Student Within-Year Retention

OUTCOMES	COEFFICIENT	AI ROBUST STANDARD ERROR	P > |Z|	[95% CONFIDENCE INTERVAL]	
Fall 2018 to Spring 2019 retention	.032	.026	0.214	-.0187046	.0836506
Fall 2019 to Spring 2020 retention	.041	.025	0.108	-.008944	.0906272

Note. The average treatment effect (ATE) estimation compares those in the matched treated group (enrolled in a PP class) versus those in the control group (did not enroll in a PP class). The Abadie-Imbens (AI) robust standard error takes into consideration the statistical variation of the estimated propensity score which is different from other methods to measure ATE when using propensity score matching.
*p < .05. **p < .01. ***p < .001.

The coefficients represent the average of the differences between observed and potential outcomes or the difference in probability that the treatment influences the outcome. For instance, the fall 2019 to spring 2020 retention rate coefficient is .041. This indicates that subjects in a PP class in the fall 2019 cohort have a higher probability of returning in spring 2020 than those subjects who did not participate in a PP class. If expressed as percentage points, subjects in a PP class are 4.1 percentage points more likely to re-enroll in spring 2020 classes as compared to nonparticipants. However, this increase in percentage points is not statistically significant as indicated by $p > .05$ and 95% confidence intervals that include zero. Confidence intervals that include a zero indicate that the null hypothesis is within the interval with a 95% confidence and that there is no statistically significant difference between groups. After propensity score matching, there is insufficient evidence to support a causal effect between participation of first-time in-college, traditional-aged students in the PP and retention and the null hypothesis cannot be rejected.

Research Question 2

Does participation in the Persistence Project influence year (fall) to year (fall) retention of first-time in college, traditional-aged students?

$H2_0$: Participation in the Persistence Project does not significantly influence year to term retention of first-time in college, traditional-aged students.

$H2_a$: Participation in the Persistence Project significantly influences year-to-year retention of first-time in college, traditional-aged students.

The estimation of the average treatment effect of the fall-to-fall retention between the matched treated and control groups was not statistically significant. Like the within term retention models, *p* values were above .05 and the 95% confidence intervals included the possibility that the null hypothesis is true (Table 16). Again, the treatment effects are positive but not statistically significant and the null hypothesis cannot be rejected. The PP does not have a statistically significant influence on fall-to-fall retention of first-time in college, traditional-aged students after using propensity score matching.

Table 16. Matching Estimates of Average Treatment Effects on Student Year-to-Year Retention

OUTCOMES	COEFFICIENT	AI ROBUST STANDARD ERROR	P > |Z|	[95% CONFIDENCE INTERVAL]	
Fall 2018 to Fall 2019 retention	.045	.031	0.148	-.0161845	.1070729
Fall 2019 to Fall 2020 retention	.023	.035	0.509	-.045165	.0910684

Note. The average treatment effect (ATE) estimation compares those in the matched treated group (enrolled in a PP class) versus those in the control group (did not enroll in a PP class). The Abadie-Imbens (AI) robust standard error takes into consideration the statistical variation of the estimated propensity score which is different from other methods to measure ATE in PSM.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

CHAPTER SUMMARY

Oakton College implemented a project to improve student within-year and year-to-year retention. Oakton's data consistently revealed increased retention for students who participate in the PP. This chapter discussed the results of a quasiexperimental study of retrospective descriptive and inferential data of two first-time in-college, traditional-aged student cohorts, fall 2018 and fall 2019. Using propensity score analysis, I answered the two research questions and failed to reject the null hypotheses. Participation in the PP did not influence the within-year and year-to-year retention of first-time in-college, traditional-aged students after using propensity score analysis. Based on the results, I made recommendations for Oakton and for future research to improve the quality of future studies and to continue the research of intentional student-faculty relationships on student retention. The study findings and recommendations are discussed in Chapter 5.

CHAPTER 5: FINDINGS AND RECOMMENDATIONS

INTRODUCTION

The purpose of this study was to determine if a program to intentionally increase student-faculty interactions during the first weeks of classes influenced the within-year and year-to-year retention of first-time in-college (FTIC), traditional-aged students. The PP includes activities that participating faculty commit to during the first six weeks of classes including holding 1:1 meetings with each student, learning students names, providing an opportunity for students to get to know one another, administering an early assessment, and providing prompt feedback on the assessment. Prior studies identify these activities as practices that increase student connectedness to the institution and sense of belonging and assist students' transition to college. This study evaluated the influence the PP had on student within term and year-to-year retention of first-time in college, traditional-aged students at Oakton by using propensity score analysis (PSA) and within the framework of Astin's input-environment-outcome impact model.

Since the inception of the program at Oakton in 2016, students who participate in at least one PP class in the fall semester are more likely to return the following spring and fall semesters. The descriptive data for the population in this study demonstrated the same pattern of increased retention as compared to those that were not in a PP class. However, the statistical analysis of retrospective observational data, using propensity score matching (PSM) to develop a counterfactual control group did not demonstrate a significant influence of the PP on FTIC, traditional-aged students within-year and year-to-year retention. In Chapter 5 I identify and discuss the major findings of the study, provides useful recommendations for Oakton, and specifies areas for future research.

FINDINGS

Student Inputs

The descriptive aggregated data of the fall 2018 and fall 2019 cohorts reflect the consistency in student inputs (covariates) and outcomes of FTIC, traditional-aged students who enroll at Oakton in the study terms (see Table 2). As noted in Chapter 4, when covariate and retention data is disaggregated for each cohort by treated (participated in the PP) and untreated (did not participate in the PP), variation in covariates (Tables 4 and 6) and retention (Tables 5 and 7) by groups and by cohort become evident. These differences in cohorts when the data is disaggregated demonstrates that students are not randomly placed into the treated or untreated groups. Since students do not know if they are registering for a class in the PP project it would appear as if the probability of being in a PP class is random. However, the differences between cohorts when comparing treated and untreated groups reinforces the need for PSA. PSA is an accepted method to study nonrandomized studies using observational data to control for selection bias by creating a counterfactual control group.

In many cases the standard deviations are larger than the means indicating a dispersion, rather than a concentration, of values, again signifying a variation in the data. This describes the diversity of the students who enroll at Oakton and reinforces that this is a nonrandomized study. When students enroll in classes, they do not know if the class is or will be a part of the PP.

In preparation for matching, the probability of placement in the PP based on a covariate linked to student retention was determined through logistic regression. The propensity regression model logit tables revealed a few covariates, standardized test scores below 1070, part-time enrollment status, high school GPA below 3.0, and no educational plan, that were statistically significant for predicting participation in a PP class. The part-time enrollment status covariate was significant in predicting assignment to a PP class for both cohorts and was negatively associated with participation in the PP. It was not unexpected for students enrolled part-time at Oakton to be less likely to participate in a PP class. Most community college students enroll in less than 12 credit hours or as part-time (Beer, 2021). In fall 2019, 66% of Oakton students enrolled part-time (NCES, 2021). By taking less classes, part-time students are less likely to engage in high impact practices (Nelson Laird & Cruce, 2009) and effective educational practices. Part-time students at Oakton are less likely to encounter a PP class.

According to Hubbard (2018), part-time students are less likely to have an educational or academic plan because many colleges present pathways to completion in a full-time semester sequence. Part-time students may struggle with creating a plan and identifying the appropriate courses to take that also fit their schedules. Educational plans are a key component of guided pathways methodology and program maps assist students in developing plans that allow them to complete credential requirements, progress, and complete on time. Students who make an educational plan are more likely to pursue more credit hours each semester (Aisen, 2021).

In the 2018 cohort, a high school GPA below 3.0 was negatively associated with participation in a PP. This was not true in the fall 2019 cohort, and instead the lack of an educational plan was negatively associated with participation in the Project. Students with lower high school GPAs may be advised to enroll in less than 15 credit hours at a community college to protect students from being overwhelmed in their first year in college (Venit, 2017). If students with lower high school GPAs are not enrolling in higher credit loads, they may be less likely to participate in a PP class. The inconsistency in the significance of the high school GPA and educational plan covariates across the fall 2018 and fall 2019 cohorts reinforces that this is not a randomized study and students do not self-select to join a PP class which introduces bias into the data.

In both cohorts, a standardized exam score below 1070 was positively associated with participation in a PP class. The current literature does not discuss any connections between SAT scores and enrollment intensity. Enrollment intensity explains the negative association between part-time enrollment and the probability of being in a PP class. It may also explain the connection between educational plans and high school GPA to participation in a PP class. However, this connection has not been studied for standardized exam scores. Another plausible explanation for lower SAT scores predicting increased participation in the PP, would be a higher number of students who attend Oakton with lower SAT scores. However, the fall 2018 cohort had similar numbers of individuals with SAT scores above and below 1070 and there were more students with SAT scores below 1070 in the untreated group. The 2019 fall cohort did have more students that had SAT scores below 1070 (*N*= 670) as compared to those with SAT scores above 1070 (*N*=500). Yet, there were more students with SAT scores below 1070 in the untreated group as compared to the treated group. There is no clear explanation as to why students with SAT scores below 1070 are more likely to be a part of the PP.

While there was relative consistency in standard errors for covariates in the logit tables, the higher standard error scores for Black, unknown race/ethnicity, and certificate seeking covariates indicate either a lower number (*N)* or skewed data. For each of these covariates the *N* was lower compared to the other covariates that had more consistent standard errors (see Table 9 and Table 10). I retrieved additional data to determine if the certificate seeking students were not retained because they earned a certificate and left Oakton. In the fall 2018 cohort, zero students earned a certificate at the end of the fall 2018 semester, and one earned a certificate at the end of the spring 2019 semester but continued to take classes at Oakton. In the fall 2019 cohort, two certificate seeking students earned certificates at the end of the fall 2019 semester. Of those, one continued taking classes at Oakton and the other student did not return. Most of the first-time in-college, traditional-aged students seeking certificates were still enrolled at Oakton in the following spring and fall semesters.

Environment

Several factors influence a student's decision to stay or leave college before they reach their goals, including academic challenges, difficulty adjusting, uncertain goals, poor involvement in the social environment, insufficient institutional fit, and uncertain educational and career goals (Harper & Newman, 2016; Tinto, 2001). For racially minoritized students, the barriers to academic and social transition to college are more daunting. Early connections are critical to students' transition to college and their level of involvement in the college environment. African American men that make these early social connections with faculty or staff members or peers increased their social capital by increasing their networks and access to resources resulting in increased persistence (Harper & Newman, 2016).

Oakton's PP attempts to address the critical first weeks of a student's time at college when students are exposed to the social and academic environment of the institution. The academic and social transition from high school to college requires connections that prevent students from never fully transitioning to and engaging with the college environment. Palmer, O'Kane, and Owens refer to an event or experience in the first six to eight weeks of college that triggers a sense of community or belongingness or a lack of sense of belongingness as a turning point. Others have identified the critical transition period as the first two to six weeks (Levitz & Noel, 1989). When students do not transition well, they are less likely to persist and ultimately may make the decision to leave college (Palmer et al., 2009; Tinto, 1993; Woosley, 2003).

Colleges provide a few programs or implement practices to a create turning point, such as first-year seminars, new student orientations, study skill sessions, learning communities, and co-curricular activities. However, colleges can be doing more to improve students' sense of belonging and assist them in getting over the anxiety related to the first class, the first assessment, the first instructor feedback, or the first doubt. Palmer et al. (1989) recommended additional turning point events or activities during the first eight weeks of classes, including expanding opportunities for students to interact with staff, peer groups, and faculty formally and informally. These interactions are crucial communication and pedagogical events that shape students' perceptions of faculty, their relationships with faculty, and retention (Wang, 2014). In a review of literature of how a sense of belonging can improve student transition to college, O'Keeffe (2013) reinforced the importance of connectedness for students transitioning to college and that a single connection with a college employee may increase a students' willingness to persist. Students who make an early connection are more likely to feel satisfaction with and a commitment to the institution.

When student-faculty interactions become a part of the college environment, informal interactions increase student satisfaction with the institution, continued progress, and involvement in cultural activities (Endo & Harpel, 1982) and the early interactions with faculty are the most critical (Pascarella et al., 1978). Oakton offers a variety of mandatory and optional turning points that may be interacting with the components of the PP to increase retention of participants in a PP class. Oakton's turning points include mandatory advising for degree-seeking students, high impact practices, college success courses, study skill sessions, and student life and co-curricular activities.

A college may not be able to control how students respond to turning point events or how other persons, such as family members, friends, partners, and employers may influence a students' decision to stay or leave college or other student inputs that influence retention. However, institutions of higher education can implement programs that intentionally increase student-faculty interactions that create academic and social environments that increase student involvement and ultimately their intent to persist.

Student-faculty interactions at the classroom level are the most critical to student retention, so any initiatives to improve student retention should start at this level (Hutto, 2017; Tinto, n.d.). Course retention and success are leading indicators of within-year and year-to-year retention (Phillips & Horowitz, 2017). To improve these leading indicators, Tinto reinforces the need to start at the classroom level, one class at a time. Tinto identifies four classroom practices faculty can implement to promote student completion. Faculty should set clear and high expectations, integrate academic and social supports into the class, provide early and frequent assessments and feedback, and engage students with them, their peers, and the institution (Tinto, n.d.). These practices are all key components of Oakton's PP.

There have been numerous calls to increase the quantity and quality of interactions with faculty to influence retention and academic achievement (Anaya & Cole, 2001; Endo & Harpel, 1982). The success of Odessa's Drop Rate Improvement Program and Oakton's PP has resulted in the Caring Campus Initiative. The initiative was created by the Institute for Evidence-Based Change (IEBC) and is being studied by the Community College Research Center. Oakton joined the Caring Campus Initiative in 2019.

Outcome

In this small study of FTIC, traditional-aged students at a single community college, the PP did not have a statistically significantly influence on within-year and year-to-year retention after propensity score matching. While I controlled for many variables that influence student retention, there may be several environmental factors, such as peer interactions and the physical environment, that can influence retention or that are interacting with the PP to increase retention as noted by Oakton since the inception of the project. The measurement of the outcome can also be influenced by the propensity score modeling methodology used to measure average treatment effects.

Propensity Score Matching Modeling

Propensity score analysis methods are meant to ensure selection bias is low or reduced when creating a counterfactual outcome group for comparison to the treatment group to determine treatment effects. This requires covariate balance before and after matching. When using traditional balancing methods, histograms and minima and maxima comparison criteria, the covariates for each cohort were balanced. Some imbalances were noted when looking at standardized mean differences of matched treated and control groups by covariate. However, for all methods of balancing there are not consistent accepted criteria to determine if a covariate is truly balanced (Austin, 2009; Yang & Dalton, 2012). The specifications of the propensity score matching model used to determine the influence of the PP on student retention can be improved to increase propensity score overlap between treated and control groups and to further reduce bias and effect size.

During covariate selection and balancing some subjects were removed from the study. The Native American/Alaskan Native covariate was removed due to low sample size, while unknown high school GPA was removed because the software indicated collinearity. Other subjects were removed prior to matching because they fell out of the minima and maxima comparison criteria or during matching because a match was not identified within the caliper distance.

Standard deviations for descriptives and inferential statistics demonstrated a wide dispersion of values for treated and untreated groups before and after matching which was evident in the histograms. This was also evident in the logit tables where some covariates had higher standard errors than most other covariates. This indicates that for those covariates, in this case, Black, unknown race/ethnicity, and certificate seeking, that either the sample size was small or that the data skewed towards high or low extremes. For both cohorts, in all three of these cases, the number was smaller than the other covariates. As a result of the data dispersion, low numbers, and possible outliers, these subjects may have been more likely to not meet the propensity score minima and maxima comparison criteria and may have been removed from the study or this may have resulted in poor match quality for these subjects.

In this study, part-time students were less likely to participate in a PP class. Most part-time students at community colleges are more likely to be Hispanic or Black (Hubbard, 2018). As a result, if these covariates resulted in propensity scores that were at the extremes they may not have been matched or they may have been removed while establishing common support with minima and maxima comparison criteria. It is important to understand who the subjects are that are not part of the study because of missing data, low samples sizes, and establishing common support.

Every attempt was made to retain as many subjects as possible. This included using missing indicator covariates, nearest neighbor matching with replacement, and applying a caliper distance during matching. When subjects are removed from a study because of modeling, the pool of subjects available for matching is reduced and the smaller sample size may result in overlooking differences that may be present, a Type 2 error (Streiner & Norman, 2012). The treatment effects for the subjects that were removed cannot be estimated (Caliendo & Kopeinig, 2008). It is important to understand the characteristics of the subjects removed from the study: covariate descriptives, probability of being in the PP, and retention.

Streiner and Norman (2012) also state that while the range of propensity scores may overlap between the treated and control groups there may be subjects in areas of high and low extreme values that may not be represented in the final matched groups. As a result, the matches may be similar, but they may not be representative of their entire group (Streiner & Norman, 2012), especially if there are a larger number of subjects removed with respect to the study population (Caliendo & Kopeinig, 2008). Caliendo and Kopeinig (2008) share three concerns associated with minima and maxima comparison when establishing common support. First, there may be subjects that don't meet the minima or maxima criteria but are sitting on the edge of the cutoff criteria that may be a match for subjects in the tails of the distribution. Secondly, Caliendo and Kopeinig were concerned with areas of the distribution where there is little overlap potentially resulting in treated subjects without matches. The third concern with using minima and maxima comparison criteria is that there may be few subjects within the tails of the distribution, again limiting the number and quality of matches.

When the match quality is poor, there may be more imbalance, model dependence, and increased bias (King & Nielsen Gill, 2019). Depending on the PSA model used, and the decisions made by me in developing the model, different estimates of treatment effects can result. This includes the methods to achieve balance by removing outliers, such as when applying minima and maxima comparison criteria. King and Nielson (2019) claim this increases imbalance because data is reduced and the distance between the matches increases. In this study, percent bias after matching did increase for some variables, indicating a potential increase in covariate imbalance but the percent bias was still within acceptable levels. However, the increase in percent bias may be an indicator of inferior match quality (Caliendo & Kopeinig, 2008).

PSA is meant to reduce bias but is not able to eliminate it as seen in a randomized control trial (RCT) because PSA cannot account for all unmeasured confounding variables. A RCT accounts for all the variables that make each group different and that may influence the outcome. The variables "that differ between groups may be responsible for the apparent relationship between the intervention and outcome" including hiding a relationship or creating one where there isn't one (Streiner & Norman, 2012). PSA effectiveness dwindles when not all the covariates are accounted for or when some are removed from a study (Okoli et al., 2014). For instance, several qualitative confounding variables that influence student retention were not accounted for including student motivation (Han et al., 2017) and attitude towards college. Students may enter college with certain predispositions that may dictate their involvement in the college environment, including with faculty (Halawah, 2006). Institutions may find it difficult to overcome these student predispositions towards college and involvement. As a result, it is important to control for this variable and the variables that are predictors of involvement, including students who were educated in the United States educational system and parents' highest educational attainment (Halawah, 2006).

Several student psychological variables influence academic performance, persistence, and involvement. These factors include autonomy, apathy, and self-efficacy and self-esteem, the latter of which are associated with motivation (Friedman & Mandel, 2009). However, Friedman and Mandel (2011) conducted a qualitative study of freshman at a four-year college that controlled for variables related to academic performance and retention to determine if motivation was a predictor of student performance and retention. Motivation, among other variables such as high school GPA and SAT scores, was not a predictor of retention. Friedman and Mandel reinforced the idea that it is difficult to predict who will stay or leave college and that there may be factors outside of the known predictors of retention that influence student retention. Motivation (Hu & Kuh, 2002) and effort that students self-generate are crucial factors to consider when studying retention and student success outcomes (Hu & Kuh, 2002; Lotkowski et al., 2004). In a qualitative study of student retention, students reported that they ultimately were responsible for making the choice to continue at an institution, even when things become difficult (Zepke & Leach, 2010a). Student predispositions, such as pre-enrollment attitude towards college and motivation are variables that can be measured and should be considered when measuring the effectiveness of initiatives meant to improve retention.

The faculty who voluntarily participate in the PP may influence the impact the Project has on student retention. Oakton's PP was instituted based on a challenge to a resistant faculty leader by Oakton's Achieving the Dream Coach. The faculty leader, who was chairperson of the Humanities and Philosophy Department, accepted the challenge and she and her department faculty piloted the program. Based on the results of the pilot and the more personal connections with students, the chairperson became an innovator and further developed the Project and recruited early adopters from across the college. McKay and Rozee describe early adopters as those that "…are likely to function as leaders, welcome new ideas, have greater empathy (can project themselves into the role of the other); they communicate effectively, are more social, expose themselves to sources of communication, are role models and respected by peers, and are likely to provide information and advice to potential adopters" (McKay & Rozee, 2004, p. 23). The characteristics of Oakton faculty who volunteer a class(es) for the PP has not been studied, neither has the impact of volunteer bias on the Project outcomes.

Faculty voluntarily include a class(es) in the PP. The volunteer nature of this Project may have drawn motivated faculty that may already implement effective educational practices or use accessibility cues that result in positive student-faculty relationships and higher student retention. Volunteers may also engage because of the recognition of the program and the modest renumeration for adjunct faculty participation.

In a review of the literature of volunteers of behavioral studies, Rosenthal (1965) identified common characteristics of volunteers: they tend to be women and are considered more extroverted, less traditional, more approval-seeking, open to change, less domineering, intelligent, more educated, and from a higher social class than non-volunteers. In a study of faculty volunteers who incorporated service-learning pedagogy, McKay and Rozee (2004) used Rogers' diffusion and adoption of innovations model to study and describe faculty volunteerism in a new program or innovation. Faculty who participated in community service learning (CSL) early identified the need for the high impact practice as a pedagogical best practice with positive outcomes. Those who chose to delay or not adopt community-service learning identified lack of time and support, concerns with the process, perceived amount of work, appropriateness to their course, and other factors specific to service learning, such as community placement factors. For those that adopted the project, they identified personal beliefs or values that aligned with the CSL program and student-centered and community-centered factors (McKay & Rozee, 2004). Typical characteristics of the early adopters of CSL included faculty that were enthusiastic to try new ideas, willing to accept risks and change, and to take on leadership roles.

RECOMMENDATIONS FOR OAKTON COMMUNITY COLLEGE

The PP incorporates a bastion of classroom best practices directly linked to students' positive transition to college and to sense of belonging, and ultimately retention. As the influence of the Project on retention and other student success outcomes are studied, Oakton should continue this low-cost, faculty-driven project to support community college students as they enter, navigate, progress through, and leave Oakton. Faculty are an extension of the institution, as a result, they reflect the mission of the institution and its commitment to supporting students and their success.

Supporting Faculty

Oakton's continued commitment to the Project is evident in its participation in the Caring Campus Initiative and the increased support for faculty. Oakton's engagement in the Caring Campus Initiative has reformed the project to increase faculty fidelity to the Project activities. Oakton supports PP team chairs and Project participants in several ways including providing the team co-chairs with class release time to manage and grow the Project. The team is financially supported to attend and present at conferences.

Adjunct faculty PP participants are able to reserve hoteling offices to hold private 1:1 meetings with their students. Adjunct faculty are also able to shift some of their required weekly office hours to earlier in the term to meet with students during the first few weeks of classes. Adjunct faculty participants receive a moderate stipend for additional office hours at the beginning of the term based on student enrollment in a PP class.

Professional Development

The PP team currently offers professional development in the form of weekly PP faculty tips in Oakton's newsletter, *Oakton Matters*, an online training course that includes onboarding and critical conversation modules, and professional development sessions during faculty orientation week at the beginning of each term. Oakton is financially supporting PP faculty participants to complete the onboarding, critical conversations, and Caring Campus training. Additional professional development opportunities for faculty can further enhance students' experiences in PP classes and in their interactions with faculty.

Oakton should consider faculty professional development that identifies and provides opportunities to hone the verbal, nonverbal, and pedagogical cues that results in substantive one-to-one meetings with faculty and that encourages additional interactions with faculty outside of the classroom. By investing in this professional development, the institution avoids costs associated with poor student-faculty interactions (Cotten & Wilson, 2006), improves the quality of the one-to-one student-faculty meetings, and positively influences student success outcomes (Shaw et al., 2016). Faculty attitudes and behaviors, as evidenced by faculty immediacy, may influence student retention because students feel respected and valued by their instructor (Neville & Park, 2019).

Faculty immediacy is indicated by the verbal, nonverbal, and pedagogical signals that an instructor uses to signify accessibility and approachability (Cole & Griffin, 2013; Cox et al., 2010). Verbal cues include communications that indicate faculty value student input, such as encouraging questions in and out of class, demonstrating concern for student learning, learning student names, providing clear and constructive feedback (Cox, 2011; Cox et al., 2010; Creasy et al., 2009; Hagenauer & Volet, 2014; Neville & Parker, 2019). Nonverbal cues include the use of vocal inflections, facial expressions, such as smiling when students are asking or answering questions, and eye contact (Cox, 2011; Creasy et al., 2009). Pedagogical cues that indicate accessibility and approachability include incorporating active learning, keeping office hours, connecting theory to practice, infusing personal stories as it relates to course content, and being flexible with the syllabus and class schedule (Cox et al., 2010; Jaasma & Koper, 1999; Neville & Parker 2019).

It is primarily the faculty member who will set the tone for the one-to-one meetings based on their accessibility cues. Several researchers have recommended that faculty give clear in class cues as to their accessibility outside of class to improve student outcomes (Lundberg et al., 2018; Pascarella et al., 1978). Clark et al.'s review of the literature identified connections between faculty immediacy and increased frequency of student use of office hours and length of interactions during the visit. Clark et al. (2002) suggest that it is the classroom environment and faculty characteristics that are indicative of high interacting teachers and student-faculty interactions outside of the classroom.

While faculty may commit to the activities of the PP, faculty may not use cues to signal willingness to engage in a substantive interaction during the one-to-one meetings or other interactions in and out of the classroom. This is a consequential barrier for racially minoritized students (McCormick et al., 2013). When students consider their interactions with faculty, they weigh the costs and benefits to these interactions (Jaasma & Koper, 1999). Faculty who lack immediacy skills may be intimidating to students and students may determine that the costs outweigh the benefits and not engage. And the benefits are significant. Students who interact with their faculty outside of class are more comfortable engaging in class (Felton & Lambert, 2020; Jaasma & Koper, 1999) and have an increased sense of belonging and satisfaction with the institution (Jaasma & Koper, 1999). Students who interact with faculty outside of class are also more likely to increase their efforts because they do not want to let the faculty member down. However, students see this as a cost, not a benefit, to interacting with faculty.

Students identify the ability to disclose and discuss personal information as an important immediacy characteristic (Clark et al., 2002). This is of particular importance to first-generation students who seek out faculty to help solve academic and personal problems (Wang, 2014). However, when students reveal personal information or problems, they may be concerned that the disclosure will impact their progression at the institution. This can lead to a breakdown of trust between faculty members and students (Jaasma & Koper, 1999). Faculty professional development on how to handle these situations, including how to direct students to the appropriate resources on campus are critical in supporting the student and the faculty-student relationship. This will contribute to the quality of student-faculty interactions outside of class. Quality of these meetings have been demonstrated to be more important to retention than the frequency of meetings (Pascarella & Terenzini, 1980) and faculty immediacy influences the quality and frequency of these interactions (Cole, 2007).

Strategic Faculty Recruitment

Finally, as the PP team considers what faculty to engage in the Project, the team should look at course enrollment patterns for part-time, certificate-seeking, and racially minoritized student groups. In this study, these student covariates had lower numbers, hence they were less likely to participate in a PP class. Yet, the majority of Oakton students attend part-time, and Oakton is seeing an increase in certificate-seeking students. Oakton's student population continues to diversify and as the college extends its reach into the more diverse areas of its district, the interests and needs of students who identify as Black, non-Hispanic should be evaluated. Oakton's current retention data indicates equity gaps and students who identify as Black and Hispanic have not met President Smith's 54% retention goal. The retention rates for Black students who participate in a PP class have higher retention rates than other racial and ethnic groups.

Continued Research

While this study did not demonstrate a statistically significant influence of the PP on first-time in-college, traditional-aged students after propensity score matching; Oakton's data continues to indicate that the Project is positively impacting student within-year and year-to-year retention. This warrants additional quantitative and qualitative statistical studies to assess the effectiveness of the program. The PP may be interacting with other environmental factors such as peer interactions, other classroom environmental factors, and the physical environment of the college (Fleming et al., 2005) to influence student retention. In the next section of this chapter, Recommendations for Future Research, I identify several ways to improve the current study and to use different modeling strategies to control for additional covariates and volunteer bias.

Recommendations for Future Research

This study was limited to the implementation of the PP at a single, pubic, Midwestern community college. While this statistical analysis did not demonstrate a statistically significant influence of the Project on the within-year and year-to-year retention of first-time in-college, traditional-aged students, there are a few findings that indicate a need for future research. Improvement in study quality will improve confidence in estimates of the influence of participation in the PP on student within-year and year to retention.

First, this study focused on a specific population of students that enrolled in courses at Oakton in fall 2018 and fall 2019. I focused on first-time in-college, traditional-aged students in part because much of the literature aims to address the importance of sense of belonging and involvement in the academic and social environments as they transition to college and make the decision to stay. I also included these students because they were required to complete new student orientation, which is not true of all students who enroll each fall. The first-time in-college, traditional-aged students who participated in the PP in fall 2018 only made up 21.1% of the total students in the project (445 out of 2113 students). Of the total fall 2019 PP student participants, 22.6% were first-time in college, traditional-aged students (475 out of 2099 students). To increase sample size and reduce effect size for covariate balancing, future research could focus on one fall cohort and include all students in the study who enrolled at Oakton that term and additional covariates to the study, including age and new student orientation participation.

The current study population could be analyzed using weighting methods, such as inverse probability treatment weighting, to offset imbalances in covariates that were evident in some balance checks, such as part-time enrollment status. Students with full-time enrollment status would be weighted differently than students with part-time enrollment status. The goals of weighting include balancing covariates to remove bias and stabilizing estimates of treatment effects when large weights may influence the treatment effects or where there are highly variable weights (Zubizarreta, 2015).

When conducting propensity score analysis, covariate selection and inclusion is critical. Studies can include upwards of 100 covariates, while smaller studies may not include this large number of variables. According to Brookhart et al. (2006), when a smaller number of variables are used it is important to focus on variables that are related to the outcome as compared to treatment assignment. Rubin (2001) supports the use of a smaller number of covariates related to the outcome if balance is checked after matching. This is a small study with a small number of covariates and balance was checked before and after matching. Balance after matching varied by the type of balancing method used. For instance, part-time enrollment status was balanced when comparing means and looking at percent bias of those in the treated group as compared to those in the control group for each cohort. However, when looking at standardized mean differences, part-time enrollment status had a small imbalance after matching for the fall 2018 cohort and a moderate imbalance after matching for the fall 2019 cohort. The study did not include all covariates that are related to retention because some are not measured by the college or are difficult to measure, such as student commitments outside of college (e.g., work, family) and motivation (Friedman & Mandel, 2011). Additional covariates that could be included in future studies are the COVID-19 pandemic (as an historical covariate), discipline or department, program of study or pathway, amount of credit for prior learning, veteran status, foreign schooling, marital status, foster status, number of dependents, and mode of instruction of class.

It is recommended that future studies of the PP using PSA include sensitivity analyses to account for any unobserved confounding variables (Rudolph & Stuart, 2018) and to determine how different PSA methods can influence variation and imbalance (Streiner & Norman, 2012). As discussed in Chapters 1 and 3, covariates that are not included in the study can contribute to omitted variable bias or unobserved confounding. There are several sensitivity analyses that can measure for measurement errors, including classical, systematic differential, and heteroscedastic analyses (Rudolph & Stuart, 2018).

There are multiple ways to match treated and untreated subjects in PSA that results in varied ways to determine distance between matches, which subjects are included in the study and treatment effects (Streiner & Normal, 2012). King and Nielson (2019) argue that the variation in estimates of treatment effects based on the PSA model used can lead to model dependence. To confirm the chosen PSA model is effective in measuring treatment effects, Streiner and Norman (2012) recommend conducting sensitivity analyses that test different propensity score matching models. If the results of these sensitivity studies are consistent researchers can be more confident in the results (Streiner & Norman, 2012).

Propensity score matching identifies a subject in the untreated group with at least one subject in the treated group who has a similar propensity score. The propensity score is the culmination of all of the covariate values into a single value and is the estimated probability that a subject will be in the treatment or control group. Subjects are matched by propensity score, not by individual covariates. Future research could include exact matching. In exact matching, subjects with identical covariate values are placed in the same bracket and treated and control subjects within the bracket are matched. For instance, students who are full-time are more likely to be in the PP and they are more likely to persist and return the following term and year (Fike & Fike, 2008). A full-time student in the treatment group could be matched with a full-time student in the control group. Any subject not matched is removed from the study. Exact matching results in balanced covariates but it is very limiting in that the results cannot be generalized outside of the final matched treated and control groups because the study sample will be small (Greifer, 2021). Exact matching on a few covariates, like full-time and part-time status, could be combined with propensity score matching on the remaining covariates to offset any decrease in sample size.

Outside of propensity score matching, additional research can focus on the role of peer interactions, characteristics of faculty participants, and qualitative analyses of students' perceptions related to the institution, sense of belonging, intent to persist, and peer interactions. A component of the PP is for faculty to create an early opportunity for students to get to know and engage with one another. Peers can either promote or block sense of belonging. Peer support has been linked to a student's positive transition to college (Brouwer et al., 2016) and it is identified as a predictor of retention (Berger & Milem,1999; Dennis et al., 2005; Morrow & Ackerman, 2012). Specifically, collaboration with peers can increase persistence and completion (McClenney & Marti, 2006), particularly when mediated by faculty (Cole, 2010). Students who feel a high sense of belonging indicate increased support and engagement when faculty provide opportunities for peer collaboration (Wilson & Gore, 2013). Some studies have indicated that peer interactions may be more influential on personal development and social involvement (Astin, 1999; Endo & Harpel, 1982) and student intent to persist and actual retention (Morrow & Ackerman, 2012) than student-faculty interactions.

Albeit faculty immediacy has been linked to quality and quantity of student-faculty interactions, other faculty characteristics may influence retention, including full or part-time faculty status, discipline of faculty, and faculty use of high impact practices. With a continued increased reliance on adjunct and part-time faculty to teach classes at community colleges, it would be worthwhile to look at the participation of faculty by status and associated retention rates. In a study of study of community college student retention and its relationship to faculty status, there was a positive correlation between part-time faculty status and course retention (Hutto, 2017), a leading indicator of within-year and year-to-year retention. Yet, part-time faculty are less likely to have interactions with students outside of class (Wirt & Jaeger, 2014) because they have decreased availability. Studies have identified that the number of classes students take with a part-time faculty member is a predictor of student year-to-year retention. Exposure to a greater degree of classes taught by part-time faculty negatively predicts year-to-year student retention (Jaeger & Eagan, 2011; Jaeger & Hinz, 2009). At least 50% of faculty who participate in Oakton's PP are adjunct faculty. It is important to support these faculty with professional development and to consider faculty status as a covariate in future studies.

Faculty also create the learning environments within academic disciplines and departments that may impact the student experience, including student-faculty interactions (Kim & Sax, 2010). Students are more successful when department faculty collectively foster supportive learning environments that result in increased student-faculty interactions and student performance. Some studies suggest that student retention varies by students' major and faculty discipline (Daempfle, 2003; Gansemer-Topf et al., 2017). This is evident in nursing programs, where small cohorts of students with a low faculty to student ratio report the positive and negative impacts mentorship and faculty accessibility and approachability can have on student attrition (Ingraham et al., 2018; Shelton, 2003). Students' program of study could be added as a covariate to the study.

Finally, the faculty use of high impact practices and effective educational practices should be considered in future studies. In a review of the literature, McCormick et al., 2013) recommend that future research look at the connection between faculty use of high impact practices on the quality of student-faculty interactions. Prior studies suggest that high impact practices are linked to increased student engagement and learning, positive perceptions of the institution, and retention (Harper & Quaye, 2014; Kinzie et al., 2008; McCormick et al., 2013). Faculty use of evidence-based classroom high impact practices could be included as another variable in future studies.

CONCLUSION

Oakton's PP generates opportunities for faculty volunteers to create environments in and out of the classroom that involve students academically and socially by including activities that have been linked to increased connectedness to the institution and others. The inclusion of intentional student-faculty interactions can result in positive outcomes such as student satisfaction with a program and the college, improved motivation and sense of belonging, resulting in increased student retention. Oakton's PP is a low-cost, faculty driven program intended to increase within-year and year-to-year student retention. Oakton's retention data of students who participate in the project as compared to those students who do not participate in the project consistently demonstrates increased within-year and year-to-year retention. This study attempted to answer two research questions and associated hypotheses:

> RQ1: Does participation in the Persistence Project influence term (fall) to term (spring) retention of first-time in college, traditional-aged students?
>
> $H1_0$: Participation in the Persistence Project does not significantly influence term-to-term retention of first-time in college, traditional-aged students.
>
> $H1_a$: Participation in the Persistence Project significantly influences term-to-term retention of first-time in college, traditional-aged students.
>
> RQ2: Does participation in the Persistence Project influence year (fall) to year (fall) retention of first-time in college, traditional-aged students?
>
> $H2_0$*: Participation in the Persistence Project does not significantly influence year to term retention of first-time in college, traditional-aged students.*
>
> $H2_a$*: Participation in the Persistence Project significantly influences year-to-year retention of first-time in college, traditional-aged students.*

The statistical model identified covariates that predicted participation in a PP class. This information can be used by Oakton to strategically recruit faculty to participate in the project to have the greatest impact on student outcomes. The study results did not support the alternative hypotheses and the null hypotheses could not be rejected. While this first statistical analysis of the Project's influence on the within-year and yearly retention of first-time in-college (FTIC), traditional-aged students was not statistically significant after using propensity score matching, additional quasi-experimental studies of the retrospective data are warranted to further reduce effect size, bias, and covariate imbalance and to determine the effects of the PP more broadly on student retention.

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APPENDIX A: FERRIS STATE UNIVERSITY IRB APPROVAL LETTER

FERRIS STATE UNIVERSITY

INSTITUTIONAL REVIEW BOARD
1010 Campus Drive FLITE 410 Big Rapids, MI 49307
www.ferris.edu/irb

Date: June 25, 2021

To: Susan DeCamillis, EdD and Ruth Williams
From: Gregory Wellman, R.Ph, Ph.D, IRB Chair
Re: IRB Application *IRB-FY20-21-157 Evaluating Program Effectivenss of a Persistence Project*

The Ferris State University Institutional Review Board (IRB) has reviewed your application for using human subjects in the study *Evaluating Program Effectivenss of a Persistence Project (IRB-FY20-21-157)* and approved this project under Federal Regulations Exempt Category 1. Research, conducted in established or commonly accepted educational settings, that specifically involves normal educational practices that are not likely to adversely impact students' opportunity to learn required educational content or the assessment of educators who provide instruction. This includes most research on regular and special education instructional strategies, and research on the effectiveness of or the comparison among instructional techniques, curricula, or classroom management methods.
Category 4. Secondary research for which consent is not required: Secondary research uses of identifiable private information or identifiable biospecimens, if at least one of the following criteria is met:

(i) The identifiable private information or identifiable biospecimens are publicly available;

(ii) Information, which may include information about biospecimens, is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained directly or through identifiers linked to the subjects, the investigator does not contact the subjects, and the investigator will not re-identify subjects;

(iii) The research involves only information collection and analysis involving the investigator's use of identifiable health information when that use is regulated under 45 CFR parts 160 and 164, subparts A and E, for the purposes of "health care operations" or "research" as those terms are defined at 45 CFR 164.501 or for "public health activities and purposes" as described under 45 CFR 164.512(b); or

(iv) The research is conducted by, or on behalf of, a Federal department or agency using government-generated or government-collected information obtained for nonresearch activities, if the research generates identifiable private information that is or will be maintained on information technology that is subject to and in compliance with section 208(b) of the E-Government Act of 2002, 44 U.S.C. 3501 note, if all of the identifiable private information collected, used, or generated as part of the activity will be maintained in systems of records subject to the Privacy Act of 1974, 5 U.S.C. 552a, and, if applicable, the information used in the research was collected subject to the Paperwork Reduction Act of 1995, 44 U.S.C. 3501 et seq.

Your protocol has been assigned project number IRB-FY20-21-157. Approval mandates that you follow all University policy and procedures, in addition to applicable governmental regulations. Approval applies only to the activities described in the protocol submission; should revisions need to be made, all materials must be reviewed and approved by the IRB prior to initiation. In addition, the IRB must be made aware of any serious and unexpected and/or unanticipated adverse events as well as complaints and non-compliance issues.

This project has been granted a waiver of consent documentation; signatures of participants need not be collected.

As mandated by Title 45 Code of Federal Regulations, Part 46 (45 CFR 46) the IRB requires submission of annual status reports during the life of the research project and a Final Report Form upon study completion. Thank you for your compliance with these guidelines and best wishes for a successful research endeavor.

Regards,
Gregory Wellman, R.Ph, Ph.D, IRB Chair
Ferris State University Institutional Review Board

APPENDIX B: OAKTON COMMUNITY COLLEGE IRB APPROVAL LETTER

Oakton Community College

Office of Research

1600 East Golf Road
Des Plaines, Illinois 60016
847.635.1967
Fax 847.635.1997

June 3, 2021

Dear Ms. Williams:

This letter is to inform you that your research proposal for the study, "Intentional Student-Faculty Interactions: Evaluating the Effectiveness of a Community College Program to Improve Student Retention," qualifies as an exempt study. Please note that you will need to notify Oakton Community College's Institutional Review Board if the research scope or personnel change.

We wish you the best as you conduct your research. If you have any questions or need further help, please contact the Office of Research and Planning at (847) 635-1967 or e-mail me at kbecker@oakton.edu.

Sincerely,

Kelly Iwanaga Becker

Kelly Iwanaga Becker, PhD
Assistant Vice President of Institutional Effectiveness and Strategic Planning