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Continuous Improvement in Higher Education: A Change Model Using Predictive Analytics to Achieve Organizational Goals

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Continuous Improvement in Higher Education: A Change Model Using Predictive Analytics to Achieve Organizational Goals

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Dedication

This dissertation is dedicated to the village of family, friends, teachers, and mentors it has taken to make this moment happen. To my brother Andy and Mom who tirelessly helped me look up the e-mails for this dissertation. To Cloud Nine Cocktail, for being the team that were always friends by choice. To Guillermo and Jim, the most patient and forgiving of dissertation committee members. To Marie, I am so lucky to have had you for an advisor; your passion for student success is a treasure. Last, but certainly not least, to Jeff for being the person that makes me want to be the best version of myself every day.

Biographical Sketch

Mary E. McLean is currently the Director of Analytics and Insights at the Rochester Regional Healthcare Family of Companies. She spent the beginning part of her career as the director of institutional research and effectiveness for three community colleges. Mary graduated with a master's degree in political science from Northern Illinois University in 2010. She earned a Bachelor's degree in political science and English from St. John Fisher College in 2008. Her research in the St. John Fisher College Ed.D. program in Executive Leadership focused on predictive analytics, specifically in higher education.

Abstract

During an era of accountability for institutions of higher education, it is increasingly important that leadership prioritize student success outcomes. Graduation and retention rates of new students have remained stagnant for years despite investment in the billions of dollars each year to affect outcomes. Predictive analytics are tools organizations can use to identify at-risk students and target them with success interventions prior to them showing signs of academic difficulty. This study modifies the Demming Plan-Do-Study-Act model by adding predictive analytics at the planning stage to make the model proactive. Institutional research and effectiveness professionals at colleges and universities across the United States were surveyed to determine the extent predictive analytics are being used. Sixty-one percent of colleges are using predictive analytics, and 88% of these institutions are using predictive analytics to identify at-risk students. By connecting at-risk student models to the strategic planning process, college and university leaders have the ability to revolutionize the academic experience by suggesting degree programs, courses, and success programs based on a student's likelihood of success.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

Institutions of higher education are under pressure to increase student retention and graduation rates. Former President Barack Obama, state governors, and accrediting bodies are calling for a “completion agenda” to increase the number of college graduates (Schnieder, 2010). Federal and state governments are expecting colleges and universities to perform, by substantially increasing their graduation rates, or face the possibility of funding losses by way of performance based funding programs.

Performance based funding ties government funds to student outcomes in higher education. As of July 2015, 36 states had some form of performance based funding in place, or in progress, for public 4-year and/or 2-year institutions of higher education or both (National Conference of State Legislators, 2015). Not meeting student outcome expectations could lead to a loss of state funds for many colleges. The federal government has created a nationwide college scorecard, which is a comparative benchmarking tool, to compare student success outcomes, such as graduation and retention rates, in its first step towards a performance funding system (College Scorecard, 2015). In addition to government pressure, the cost of retaining students during a time of enrollment challenges and shrinking applicant pools is another challenge for institutions of higher education (Schneider, 2010). Higher education executive leaders must look to new, innovative approaches to meet the growing demand for increased student success outcomes.

Performance Based Funding

For decades public institutions received state appropriated funding support based on varying calculations of student headcount and/or student credit hour enrollment. Successful student outcomes, such as degree attainment or transfer, were traditionally not taken into consideration. In 2009 the federal government first announced the American Graduation Initiative, which called for an additional five million college graduates by 2020 (Brandon, 2009). In 2013, former President Obama announced a performance based funding plan that would:

1. Tie financial aid to college performance, starting with publishing new college ratings before the 2015 school year.
2. Challenge states to fund public colleges based on performance.
3. Hold students and colleges receiving student aid responsible for making progress toward a degree. (The White House Press Secretary, 2013)

President Obama did not receive support from Congress for this plan, but he did have a College Scorecard established that compares institutions based on performance metrics so that students and parents can access the information while making college selection decisions. The interest in performance based funding has led 36 states to create some form of performance based funding for their public institutions (National Conference of State Legislators, 2015).

Performance based funding is a funding model for public institutions of higher education where state funding is appropriated based on how the institution is meeting educational goals such as retention and completion (Hillman, Tandberg, & Gross, 2014). This accountability movement was created to increase educational outcome achievements by incentivizing colleges to focus on graduation success rather than increasing enrollment (Burke, 2002; Heinrich, 2002). Meeting identified metric goals, such as increased degree completion, results in the reward of base appropriations or in bonus funds beyond base appropriations (Hillman, Tandberg, & Gross). Despite state and federal support for performance based funding, current research has found little evidence to support that performance based funding increases student success outcomes (Hillman, Tandberg, & Gross; Dougherty & Reddy, 2011; Sanford & Hunter, 2011; Shin, 2010; Volkwein & Tandberg, 2008). Regardless of evidentiary support, the number of states creating performance based funding systems is increasing and putting pressure on institutions of higher education to increase student success metrics, such as retention and graduation rates.

Stagnate Retention and Graduation Rates

Student retention refers to whether a student returns to the same college for a subsequent semester. According to the Integrated Postsecondary Education Data System (IPEDS) student retention is defined as, "the percentage of first-time bachelors (or equivalent) degree-seeking undergraduates from the previous fall who are again enrolled in the current fall . . . or successfully completed their program by the current fall" (2015). According to IPEDS (2015), 72% of first-time undergraduate students at 4-year institutions will return to school the next fall at the same institution. The fall-to-fall retention rate of community college students is 13 percentage points lower than 4-year institutions at 59% (Digest of Education Statistics, 2014). As demonstrated in Table 1.1, there have been minimal gains made to increase student retention rates since 2007.

Table 1.1

IPEDS Retention of First-Time Degree-Seeking Undergraduates at Degree-Granting Postsecondary Institutions, 2007 - 2013

	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012
Overall	71.3%	71.7%	71.8%	71.7%	71.8%
4-year Institutions	76.6%	77.8%	78.7%	78.9%	78.8%
2-year Institutions	61.0%	60.0%	60.8%	59.9%	59.0%

Note. Adapted from "Digest of Education Statistics," 2014.

Table 1.1 shows that overall retention rates for 2-year and 4-year colleges have increased just 1.6 percentage points over 6 years. Four-year institutions individually increased retention three percentage points over the same time period. Whereas retention rates at 2-year institutions decreased one percentage point. Graduation rates for both 4-year and 2-year institutions face similar stagnation.

After 6 years at 4-year institutions an average 55% of students will graduate with a bachelor's degree. At 2-year institutions, an average 29% of students will complete a degree after 3 years (Digest of Education Statistics, 2014).

Table 1.2

Graduation Rates from First Institution Attended within 150% of Normal Time for First-Time, Full-Time Degree/certificate-seeking Students at 2-year Postsecondary Institutions, 2005 through 2010

	2005 Cohort	2006 Cohort	2007 Cohort	2008 Cohort	2009 Cohort	2010 Cohort
2-year Institutions	27.5%	29.2%	29.8%	31.2%	31%	29.4%

Note. Adapted from "Digest of Education Statistics," 2014.

Tables 1.2 and 1.3 show minimal gains in graduation rates for both 2-year and 4-year institutions at 150% of normal completion time, which is 3 years for 2-year students and 6 years for 4-year students.

Table 1.3

Graduation Rates from First Institution Attended for First-Time, Full-Time Bachelor's Degree-Seeking Students at 4-year Postsecondary Institutions, Selected Cohort Entry Years, 1996 through 2007

	2002 Cohort	2003 Cohort	2004 Cohort	2005 Cohort	2006 Cohort	2017 Cohort
4-year Institutions	52.3%	53.2%	54.1%	54.2%	54.9%	55.1%

Note. Adapted from "Digest of Education Statistics," 2014.

Graduation rates at 2-year institutions increased 1.9 percentage points over six cohorts. Graduation rates at 4-year institutions increased slightly more at 2.8 percentage points. The lack of change in retention and graduation rates at both 2-year and 4-year institutions has occurred at the same time taxpayers and students are spending more money than ever to support education expenses.

Cost of Poor Outcomes

Poor educational outcomes cost the federal government, state government, institutions of higher education, and students of higher education billions of lost dollars.

Federal and state losses. The federal and state governments survive financially by collecting tax revenue. A portion of this tax revenue is dependent on citizens finding employment, paying taxes, and spending money. One reason governments invest in education is to receive return later through tax revenue from better educated and therefore more profitable citizens.

Between 2003 and 2008 it is estimated that state and federal taxpayers spent over $6.2 billion on new students who did not persist to their second academic year (Schneider, 2010). In addition, over $1.4 billion of state grants and $1.5 billion of federal grants were given to students who only attended college for one year (Schneider). Students who were not retained into their first year continue to cost the government dollars in the form of lost income and tax revenue. According to Schneider and Yin (2011):

> For students who started in Fall 2002 as full-time students seeking a bachelor's degree but failed to graduate six years later, the cost to the nation was approximately: $3.8 billion in lost income; $566 million in lost federal income taxes; and, $164 million in lost state income taxes. These estimated losses are for one year and for one class of students. (p. 2)

These funds are contributions, collected through state and federal taxes that are wasted on students who do not complete their education.

The federal government gives colleges money for programs to remediate at-risk students. The cost of college remediation programs is estimated at $2.3 billion each year (National Conference of State Legislatures, 2015) and cost for federally funded student success programs, such as TRIO, is over $800 million dollars (Council for Opportunity in Education, 2015). TRIO are:

> Federal outreach and student services programs designed to identify and provide services for individuals from disadvantaged backgrounds. TRIO includes eight

> programs targeted to serve and assist low-income individuals, first-generation college students, and individuals with disabilities to progress through the academic pipeline from middle school to post baccalaureate programs. (U.S. Department of Education, 2016).

Despite these remediation programs, student success rates are not changing. In addition, there is a substantial cost college and universities are paying for unsuccessful students.

Higher education losses. The Delta Cost Project (Johnson, 2012) measured the cost of lost students for institutions of higher education based on total instructional expenditure per student. According to Johnson (2012):

> By linking the records of students in the BPS (Beginning Postsecondary Students Longitudinal Study) survey to the institutions they attended, and by using data on months of full-time and part-time enrollment from the survey, we were able to estimate total instructional and related expenditures for ninety-five percent of both dropouts and completers in the survey. (p. 5)

The Delta Cost Project found the average cost to an institution per non-retained student is $26,572 for public 4-year institutions, $14,730 for 2-year institutions, and $32,603 for private 4-year institutions. When one accounts for the fact that 4-year institutions are losing an average 20% of first year students and 2-year institutions are losing an average 40% of first year students the cost per non-retained student is very high. In addition, research shows it costs institutions of higher education more to recruit new students than it does to retain them (Ackerman & Schibrowsky, 2007). Replacing lost students is an additional loss to the college, in addition to the lost instructional costs.

In addition to government, taxpayer and institutional losses, the unsuccessful students also face financial burdens.

Student losses. According to the U.S. Department of Education (2016) the cost of higher education increased 28% from the 2003-2004 school year to the 2013-2014 school year across all institution types. At the same time, the total national student loan debt has increased to over $1.3 trillion (Berman, 2016). The average 3 year student loan default rate for all schools was 14.7% in 2013 (2010 cohort) and has decreased to 11.8% in 2015 (2012 cohort) (U.S. Department of Education, 2015). Students with no degree are most likely to default on their student loans (National Center for Education Statistics, 2009). In addition, over the course of one cohort of unsuccessful student's lifetime $3.8 billion dollars will be lost collectively among them in lost potential wages (Schneider & Yin, 2011). The rising cost of higher education and heavy student loan debt burdens unsuccessful students who stand to earn less over the course of their careers. At a time of increased accountability, poor student outcomes, and rising tuition and student loan debt it is imperative that college and universities produce better outcomes for their students. Identifying at-risk students and providing intervention for them to increase success rates is imperative. One emerging field offers institutions the ability to identify at-risk students before they show signs of academic difficulty and allow faculty and staff crucial time needed to help. That field is predictive analytics.

Analytics

Big data refers to information or database system(s) that store large quantities of information or data (Picciano, 2012). This data is used by college or university institutional researchers to study patterns of student performance (Picciano, 2012), often using descriptive statistics. According to Picciano, “Analytics is the science of examining data to draw conclusions and, when used in decision making, to present paths or courses of action” (p. 11). Descriptive statistics can be used as postscript descriptions of students, but cannot be used as proactive decision making tools. Recent studies indicate it becomes increasingly difficult to intervene successfully the longer a student goes without intervention (Campbell & Mislevy 2013). Predictive analytics are a proactive data tool that can empower institutions of higher education to identify at-risk students before or immediately following the first signs of difficulty.

Predictive Analytics

Predictive analytics are a “statistical analysis that deals with extracting information using various technologies to uncover relationships and patterns within large volumes of data that can be used to predict behavior and events” (Eduventures, 2013). Institutions leading the use of predictive analytics in higher education, such as Purdue’s Course Signals Project, stress the importance of connecting student success interventions, mainly academic advising or mentoring, to the at-risk student models (Educause, 2012; Pistilli & Arnold, 2010). By identifying students before or right after the first signs of trouble, predictive analytics allow advisors or faculty members to intervene quickly and more efficiently based on the issue(s) the student is exhibiting (Pistilli & Arnold). Predictive analytics bring the value of time, because they have the ability to identify students at-risk of failure before the student shows any issue.

Problem Statement

As previously mentioned, the federal government and state governments are calling for increased student success outcomes from institutions of higher education

(Schnieder 2010). Seventy-two percent of states have performance based funding in place or are in the process of creating performance based funding systems to increase accountability for institutions of higher education (National Conference of State Legislators, 2015). Increased accountability is necessary because there have been minimal gains made to student retention and graduation rates (Digest of Education Statistics, 2014). The cost of higher education is increasing and has created a student debt bubble of over a trillion dollars (Berman, 2016). Students who do not complete a degree are the most likely to default on their student loans (National Center for Education Statistics, 2009). Institutions of higher education are receiving more tuition dollars than ever, but are not meeting their obligation to see students through to graduation. Colleges that do not find a way to impact retention and graduation rates face the threat of decreased funding. Higher education leaders need to look to innovative strategies to identify at-risk students early to continuously improve outcomes. Predictive analytics offers this opportunity.

Theoretical Rationale

Continuous improvement is the theoretical framework for this dissertation. Continuous improvement is based on the belief that everything can be improved through the cyclical assessment of outcomes (Hamel, 2010). Continuous improvement is a quality management process. According to Csizmadia (2006):

> The term ‘quality management’ is a general term that encompasses policies, concepts, approaches, ideas, systems and processes designed for ensuring the systematic maintenance and enhancement of quality within an institution ensuring

the systematic maintenance and enhancement of quality within an institution. (p. 24)

Quality management is a change process that is operationalized through different models. Models that operationalize continuous improvement look different depending on the business sector, but are always based on a continuous loop cycle (Hamel, 2010).

Continuous improvement was originally proposed by Walter A. Shewhart in 1931 (Brown & Marshall, 2008). Shewhart created an improvement cycle that is commonly known as the Deming Cycle because W. Edwards Deming popularized the cycle during his career (Best & Neuhauser, 2006). The Plan-Do-Study-Act (PDSA) cycle is a continuous improvement process focusing on the constant evaluation of intervention. The four stages of the cycle are illustrated in Figure 1.1 and explained as follows:

Plan: identify what can be improved and what change is needed

Do: implement the design changes

Study: measure and analyze the process or outcome

Act: if the results are not as hoped for. (Best & Neuhauser, 2006)

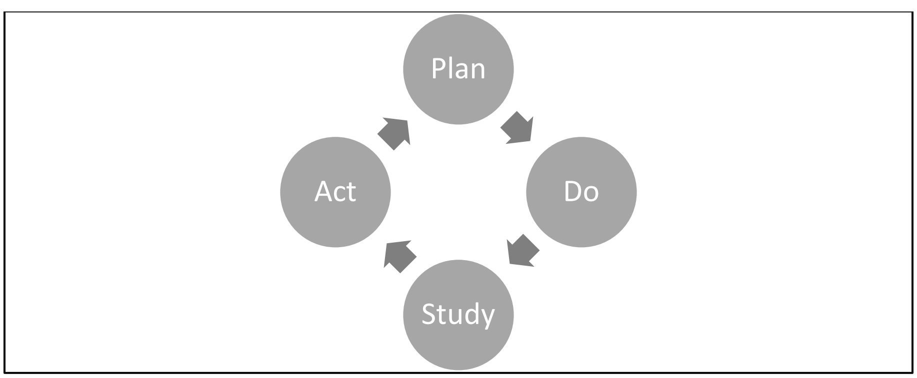

Figure 1.1. Plan-Do-Study-Act Cycle. Adapted from Best, M., & Neuhauser, D. (2006). Walter A Shewhart, 1924, and the Hawthorne factory. Quality & Safety in Health Care, 15(2), pp. 142–143.

This dissertation focuses on the planning and doing stages of the PDSA Cycle because they offer the opportunity for colleges to plan student success strategies and implement them. However, this dissertation argues that the current PDSA process has perpetuated stagnate student success rates and should be modified to include predictive analytics in the planning stage of the cycle so that the strategies planned for at-risk students can be formulated and implemented faster and targeted specifically to the students who need intervention the most.

Continuous Improvement in Higher Education

Continuous improvement is important to higher education because the six regional accreditors, Middle States Commission on Higher Education, New England Association of Schools and Colleges, Higher Learning Commission, WASC Senior College and University Commission, Southern Association of Colleges and Schools, and Western Association of Colleges and Schools (Council for Higher Education Accreditation, 2016), explicitly use continuous improvement as the process by which institutions of higher education are evaluated. Gaining and maintaining accreditation through one of these agencies is necessary if a college or university wants to receive federal student aid dollars (U.S. Department of Education, 2016). Each accreditor has some form of self-study with peer review process to gain and maintain accreditation (Ours & Swartzlander 2008).

The four main activities of the self-study with peer review process mirror the PDSA cycle are: "1. Internal self-evaluation [plan]; 2. Self-study report [do]; 3. Peer-review process [check]; 4. Implementation of peer-review recommendations and other improvements identified [act]" (Lillis, 2012, p. 63). Terminology shifts by the accreditors led to the continuous improvement process often being called institutional effectiveness on college campuses.

In 1984, the Commission on Colleges (COC) of the Southern Association of Colleges and Schools (SACS) first introduced the term institutional effectiveness into accreditation requirements (Head, 2011). “Institutional effectives [is] a process by which the institution gathers and analyzes evidence of congruence between its state mission, purposes, and objectives and the actual outcomes of its programs and activities (Sheldon, Golub, Langevin, St. Ours, & Swartzlander, 2008, p. 17). Figure 1.2 demonstrates the cyclical, or continuous, nature of institutional effectiveness, as modeled by SACS, which follows the PDSA cycle at each step.

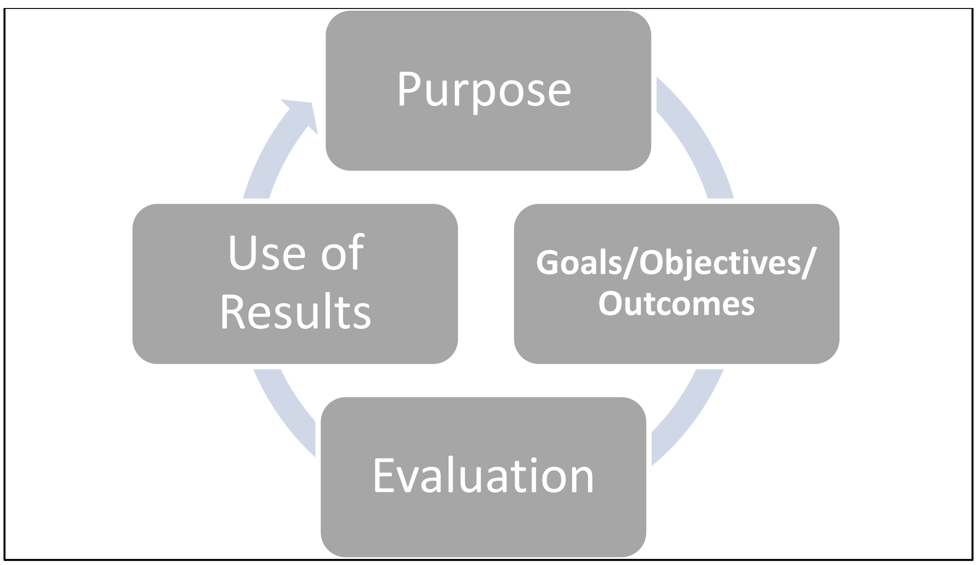

Figure 1.2. The Cyclical Nature of Institutional Effectiveness. Adapted from Head (2011)

The inputs to institutional effectiveness processes include: “Accreditation standards . . . (the) institution’s mission and goals, and data on student learning and other outcomes” (Dodd, 2004, p. 14). While accreditors require evidence to show that institutional effectiveness processes are occurring on a college campus, they are not prescriptive about how a college should accomplish institutional effectiveness (Griego, 2005). Thus, institutional effectiveness is modeled differently at each institution.

While continuous improvement and institutional effectiveness models have been the basis of higher education accountability for decades, student success outcomes have not changed. This dissertation proposes modifying the PDSA cycle, of which continuous improvement in higher education is based upon, by adding predictive analytics to the planning stage so that at-risk students can be identified early and targeted strategically in the “Do” stage of the process. The modified cycle is modeled in Figure 1.3.

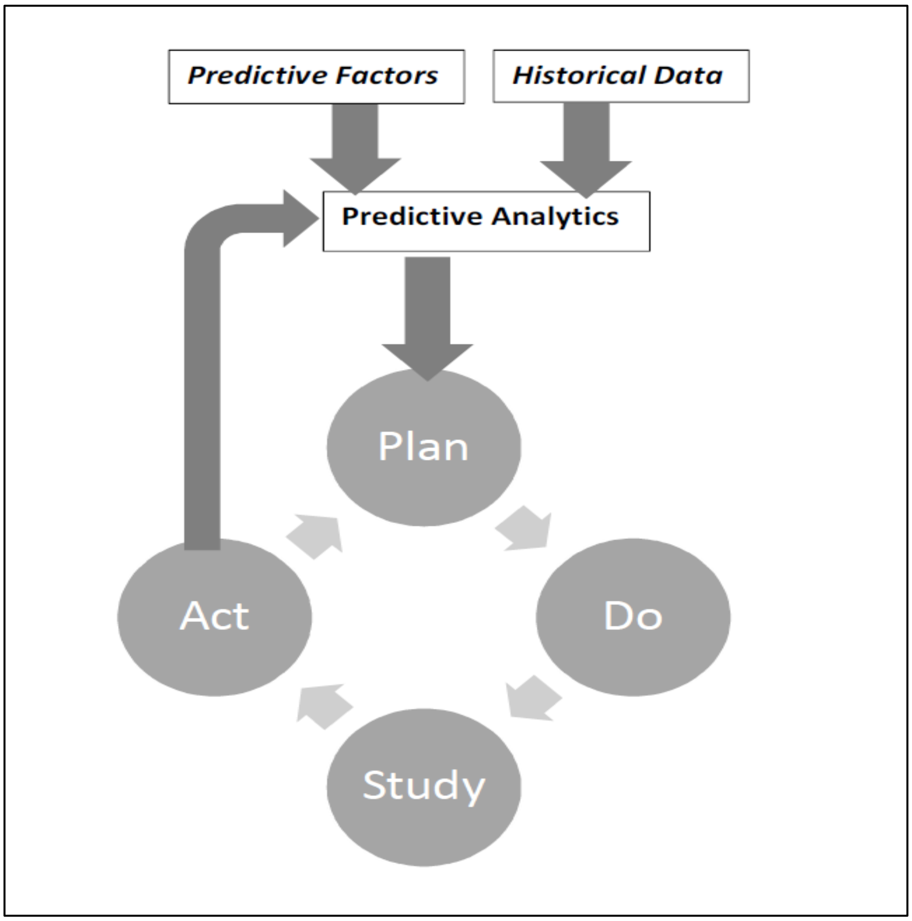

Figure 1.3. Plan-Do-Study-Act Cycle with Predictive Analytics.

This modified process offers higher education the opportunity to become proactive with the use of data, rather than the traditionally reactive approach to data use that higher education has always employed (Bichsel, 2012) and the current PDSA process has encouraged. Predictive analytics can inform the planning process. After intervention, the predictive models can be retrained to become even more precise in the "Study" stage for the next implementation.

Statement of Purpose

The purpose of this study is to understand how colleges and universities are using predictive analytics, and to explore what strategies have been used to facilitate or prohibit the use of predictive analytics with student success intervention on college campuses. Predictive analytics has proven to be a successful performance improvement tool for private industries (Siegel, 2016), but limited research exists on the use of predictive modeling in higher education. Higher education has historically used descriptive statistics to look at institutional data. However, descriptive statistics are reactive measures of performance. Predictive analytics allow institutions to provide proactive targeted interventions towards specific at-risk students quickly. Little research exists to show how colleges are using predictive analytics. Furthermore, no research exists to explain the catalysts and barriers to successfully using predictive analytics on college campuses.

Research Questions

The primary research questions this study will answer are:

1. Are colleges and universities using predictive analytics to identify at-risk students and provide student success interventions?
2. How are predictive analytics being used on college campuses?
    a. How are they used with student success interventions on college campuses?

3. What strategies are being used to facilitate or prohibit the use of predictive analytics with student success intervention?

The study will also look for similarities and differences that might exist in how 2- and 4-year and private/public institutions are using predictive analytics.

Potential Significance of the Study

This study contributes to an emerging field of research on analytics in higher education. Most existing studies are case studies of individual institutions that describe the model created and its accuracy (Kappe & Flier, 2012; Sadler, Cohen, & Kockesen, 1997; Smith, Lange, & Huston, 2012; Xueli, 2009). Little research exists on how predictive analytics are being used in higher education. This study tells us that predictive analytics are being used at most colleges and universities in the United States. We now know what functions predictive analytics are being used for and at what rates. The factors and college personnel important to the adoption of predictive analytics have been identified. In addition, colleges that are using predictive analytics to identify at-risk students are connecting them to success interventions.

Definitions of Terms

In the emerging field of analytics in higher education, definitions of key terms is scattered and varied. Analytics may refer to topics of interest, intent of the activity, or an object of analysis; however, higher education is often inconsistent with its use of the term analytics (van Barneveld, Arnold, & Campbell, 2012). As noted in van Barneveld, Arnold, and Campbell, “Hawkins and Watson caution that analytics is not a one-size fits all endeavor and that one has to consider that analytics is a goal-direction practice. . . analytics means different things to different people” (p. 2). There are three similar analytics terms that are inconsistently used in higher education literature but all have similar attributes: predictive analytics, academic analytics, and learning analytics. While used inconsistently, the use of predictive algorithms is at the core of each higher education analytics term. The ability to detect relationships between variables and predict students who will have academic difficulty and interpret the information into a proactive resource for faculty and staff is behind predictive analytics, academic analytics and learning analytics (van Barneveld, Arnold, & Campbell). Thus, the literature may refer to any of the three of these terms, for the purposes of this dissertation they are to be treated the same, unless otherwise noted. Their collective definition is to "leverage an organization's business knowledge by applying sophisticated analysis techniques to enterprise data. The resulting insights can lead to actions that demonstrably change [behavior]" (van Barneveld, Arnold, & Campbell, 2012, p. 4).

Chapter Summary

Continuous improvement is the accountability process used to evaluate institutions of higher education, but the overall retention rates for 2-year and 4-year colleges have increased just 1.6 percentage points over 6 years (Digest of Education Statistics). During a similar time period, $6.2 billion of state and federal taxpayer money and $2.9 billion of state and federal grants were spent on not retained students (Schneider, 2010). An average of $24,635 will be lost per not retained student by 2-year and 4-year institutions (Johnson, 2012). Large amounts of taxpayer and tuition dollars are being spent on students who do not return for their second year of college. At a time of increasing accountability, higher education leaders can look to innovative tools, such as predictive analytics, to identify at-risk students and target them with success intervention.

There is little research on the use of predictive analytics in higher education. The research that does exist provides evidence that predictive analytics can be used to successfully increase student success rates when combined with intervention. It is important to gain an understanding of how predictive analytics are being used on college campuses across the nation. In addition, little is known about what factors facilitate and prohibit the successful implementation of predictive analytics in higher education.

Chapter 2: Review of the Literature

Introduction

Continuous improvement literature gained attention in the 1970s as Japan became a manufacturing industrial power by following continuous improvement processes, as prescribed by Deming's Total Quality Management (TQM) model based on the PDSA Cycle (Hansen, 1993). The successful implementation of quality processes in manufacturing led to the introduction of the TQM model in higher education in the late 1980s (Sallis, 1993). The purpose of continuous quality improvement processes is to systematically assess program implementation and outcomes to improve the delivery of services (Sallis).

Continuous improvement literature in higher education peaked in the 1990s with case study examples of its principles applied to the academy—many of which are cross continental examples (Owlia & Aspinwall, 1996; Birnbaum & Deshotels, 1999; Hansen, 1993). Over time the six regional accreditors started to require quality improvement as part of the reaccreditation process did the terminology and expectations of improvement in higher education begin to change. Most recently, continuous improvement is known as institutional effectiveness and is thought of as an accreditation expectation, rather than an organizational quality model. Empirical studies examining continuous improvement have been reviewed to lay a framework for this dissertation.

Continuous Improvement Literature

In a cross sectional survey of Spanish firms, Garcia-Bernal and Ramirex-Alexson (2015) sought to answer why and how Total Quality Management (TQM) leads to performance improvement. The researchers note there is disagreement in the literature on why and how improvements are derived from TQM and who actually benefits from the processes (Garcia-Bernal & Ramirex-Alexson).

> The main contribution in this paper is that the authors explain the path from TQM adoption to organization performance, clarify the goals organizations may be pursuing when adopting organizational innovations such as TQM, and identify who the beneficiaries are and why and how they benefit from TQM. (Garcia-Bernal & Ramirex-Alexson, 2015, p. 24)

This study provided support that the TQM model can have a direct and positive effect on the operational performance of organizations (Garcia-Bernal & Ramirex-Alexson). Operational performance is directly related with positive customer satisfaction, employee satisfaction, and financial performance (Garcia-Bernal & Ramirex-Alexson). All the findings were noted as consistent with previous research. This study is important to the state of the science because it shows empirical research on performance outcomes using quality improvement models is possible.

Using a content analysis methodology, Pratasavitskaya and Stensaker (2010) investigated quality management literature in higher education between the years 1995 and 2008. They note the lack of empirical studies on this topic and explain that "analysis of models or approach of quality assurance at the institutional level is rarely addressed" (Pratasavitskaya & Stensaker, 2010, p. 37-38). Citing competing scholarly concerns over the implementation of quality management in higher education (Brookes & Becket, 2007; Harvey (1995), the purpose of their study was to examine potentials and problems in the research conducted on quality management in higher education. They sought to: “identify possible approaches to quality management; discuss whether and how different approaches share similarities as to how quality management is perceived; and, suggest possible areas for development…” (Pratasavitskaya & Stensaker, 2010, p.38).

Pratasavitskaya and Stensaker (2010) found that most articles claimed to present continuous improvement models but were mostly investigations or case studies of quality management. Pratasavitskaya and Stensaker found four characteristics regarding the way quality management is understood and theorized. First, quality management literature is very heterogeneous and filled with case studies that advocate possible transferability of findings, but do not build their frameworks from close examination of previous research (Pratasavitskaya & Stensaker). A second and inconsequential finding was that most articles reviewed covered more than one analytical category (discussed in methodological review) by Brennan and Shah. Third, the reviewed literature shared a common purpose of enhancing the student learning experience when defining quality. Finally, most reviewed articles “emphasize the need for different management measures to coordinate the educational processes at all levels of a higher education institution…[and] gave leadership an important role in creating…a collegial culture in order to achieve transformation of the learners” (Pratasavitskaya & Stensaker, 2010, p. 47). Leadership is inherently important to improving student outcomes in higher education. Higher education leaders direct planning and budgetary investment.

Brookes and Becket (2007) also conducted a content analysis of quality management approaches in higher education environments. This study categorized the political, economic, and sociocultural factors that drive higher education institutions to prioritize quality management (Brookes & Becket).They are that benefits of models include the requirement of institutions and departments to participate in structured quality management processes and the prioritization of such efforts (Brookes & Becket). However, the authors placed strong emphasis on the limitations of these approaches, suggesting that current quality models were designed for industry, which could lead to a "culture of managerialism in higher education" (Brookes & Becket, 2007, p. 4). The limitations of applying quality improvement models designed for private industry include: bureaucratic structures in higher education undermine the implementation of these models; the models rely on team based approaches that "is proving contentious to the traditional autonomous role of academics;" and, "there is an inherent difficulty in quantifying the outputs of higher education for self-assessment purposes" (Brookes & Becket, 2007, p. 21). Further, these models appeared to be geared toward non-academic units in higher education and limited in effectiveness by responding primarily to accountability agencies (Brookes & Becket). Thus, the researchers suggest that rethinking current approaches to quality management needs to occur with a prioritization of teaching and learning and that the cause of the misplaced emphasis is using private industry models in higher education. Further review of the institutional effectiveness literature provides some support for Brookes and Becket's findings that there is difficulty in quantifying outputs, but research has shown that continuous improvement efforts in higher education are not just for administrative units.

Action inquiry. In their case study, Edward, McKinney, and Tuttle (2006) argued that systematic quality improvement research has not kept up with changes in higher education planning. They argued that assessment methods have been responsive to accountability systems and funding agencies and therefore focus on the front end of change (Edward, McKinney, & Tuttle). Meanwhile, assessment methods have not generated many evaluations of the improvement efforts; this is consistent with the review of the literature. Furthermore, Edward, McKinney, and Tuttle argue:

> It is possible that the adaptive change model [continuous improvement models] that has evolved in higher education—using strategic methods to scan research to inform adaptive changes—works to address many of the challenges that come up…Efforts to improve retention have also implicitly used this strategic approach. Interventions have evolved based on an understanding of the research, but evaluations of those interventions are rare…While strategic action may be appropriate for mission-oriented planning and for adaptive changes, it may not be the best approach to solving the most serious problems. (p. 64)

The researchers caution that not understanding the underlying causes of serious problems, though they do not say what those problems are, would be most problematic when addressing educational challenges of nontraditional populations. Thus, they argue for an action inquiry approach to addressing critical challenges. At time of publication, this study (Edward, McKinney, & Tuttle, 2006) was at the midpoint of the action research project and did not have summative results to share.

Self-study with peer review. The self-study with peer review process continues to be the model for continuous improvement in the institutional effectiveness landscape.

However, Lillis (2012) cites the lack of empirical research demonstrating the effectiveness or impact of this process on the institutional level. Cost, length of the process, and staff time commitment are limitations to this approach, such that it is important to ask if it is worth the investment. Thorn (2003) found that the self-study and peer review process had two positive results: increased awareness of strategic planning and acting as a forum for staff to provide input to decision making processes. Lillis' (2012) study focused on the quality assurance instruments that assess effectiveness core activities. Specifically, "the question being addressed is to what extent these instruments can be trusted" (Lillis, 2012, p. 60). Lillis found that the programs at three institutions were implemented as intended, fulfilled a substantial majority of their objectives, peer reviewed recommendations were completed, and informants also thought the programs were effective. This study provides evidence that quality improvement instruments can be trusted.

Continuous improvement and student outcomes. In their case study, Jenicke, Holmes, and Pisani (2013) applied the continuous improvement model Six Sigma, a data-driven defect eliminating model, to undergraduate retention in a college of business. Jenicke, Holmes and Pisani study presents an applied model of the Six Sigma model to institutional processes affecting retention. While this study does not provide quantifiable changes made as a result of the applied model, it does demonstrate that continuous improvement processes in higher education emphasize data and interventions to improve outcomes. The researchers note that the Six Sigma model is widely used in private industry but has been rarely used in higher education environments; it has great potential to produce results with high-risk populations in higher education (Jenicke, Holmes & Pisani).

Brown and Marshall's (2008) case study used the PDSA Cycle to explore the impact of a quality improvement model in the Department of Nursing at Norfolk State University (NSU). The NSU Nursing Department used data and research extensively in their planning stage of the cycle. Clear goals were set to increase the nursing licensing exam pass rate, program graduation rates, and student and employer satisfaction (Brown & Marshall, 2008). A number of strategies were used in the action phase of the model, including strategies for student engagement, strategies for faculty engagement, and departmental research projects (Brown & Marshall). Data was again used in the check phase of the model. Exit exam pass rates, licensure rates, and feedback from students and faculty were analyzed. Finally, in the act phase the faculty revised curriculum, increased activities for student involvement, and requested a student adviser position for the program based on the first phase of results (Brown & Marshall). Brown and Marshall's study is particularly unique because it shares the outcomes of the implemented improvement model. According to Brown and Marshall, "significant improvement in the NCLEX-RN (nursing licensure exam) performance for associate degree students was achieved after the first year of the quality improvement plan. First-time NCLEX-RN pass rates increased from 56% in 2004 to 87% in 2005" (2008, p. 210). Anecdotal reports from area employers suggested that employer satisfaction increased; and, small improvements in student satisfaction rates were recorded (Brown & Marshall).

The results of this case are particularly interesting because it demonstrates that successful implementation and results from quality improvement models can be found at institutions with at-risks students. Brown and Marshall report that NSU students are typically first generation, low income, minority students who work while going to school. If quality improvement models successfully facilitate documented improvement outcomes at an institution with the most high-risk of students, then they should be applicable in other higher education contexts. In addition, if the PDSA Cycle, modified with predictive analytics, was used to identify the at-risk nursing students prior to the planning stage, it is possible that the student success rates would be even higher.

Jenkins (2007) hypothesized that community colleges would be more effective institutions if they:

> Have an institutional focus on student retention and outcomes, not just enrollment; offer targeted support for underperforming students; have well-designed, well-aligned, and proactive student support services; provide support for faculty development focused on improving teaching; experiment with ways to improve the effectiveness of instruction and support services; use institutional research to track student outcomes and improve program impact; and, manage the institution in ways that program systematic improvement in student success. (pp. 949-950)

These hypotheses were connected by the idea that effective community colleges manage programs and services in a methodical manner to impact student success (Jenkins). Additionally, targeting student support services to specific minority student needs showed positive success results. Jenkins suggests that managing and aligning programming and services to support student success is more important than the bureaucratic policies of institutional effectiveness. However, the high-impact colleges had well developed college-wide improvement systems in place based on research and data (Jenkins). Thus, while Jenkins research supports the importance of student support services to student success, it should not go unappreciated that the most successful schools had strong continuous improvement models in place.

Institutional Effectiveness

As explained in Chapter 1, institutional effectiveness is the continuous improvement process used by higher education accrediting agencies. Head and Johnson (2011) completed descriptive case studies of each accreditation agency's institutional effectiveness process.

The accreditors. While accreditation is often viewed as a bureaucratic requirement, the researchers note several benefits to institutions, including:

> It verifies compliance with certain predetermined, common standards of excellence; it can protect an institution from unwarranted criticisms and, to the extent that the faculty is involved, provide the stimulus for improvement of courses and programs; it promotes internal unity and cohesiveness; students are in an improved position when it comes to judging various institutions and program; and a college or university may more accurately ascertain the value and equivalence of transfer credits. Finally, accreditation assists in meeting one of several potential criteria for obtaining federal funding and assistance. (Head & Johnson, 2011, p. 37)

By focusing on these benefits, rather than the enforced nature of accreditation standards, Head and Johnson provide examples "that may help practitioners build an institutional mind-set that the reason for determining expected outcomes and assessing those outcomes is to give the institution the actionable data needed to move forward" (2011, p. 51).

Head and Johnson (2011) note that the Middle States Commission on Higher Education has two standards related to effectiveness but is not prescriptive (similar to others) in how to implement and assess the institutional effectiveness of an institution. Both Standards 7 (Institutional Assessment) and Standards 14 (Assessment of Student Learning) are based on a cyclical process of improvement (Head & Johnson). This cyclical and non-prescriptive process is important as it relates to why many quality improvement studies in higher education are case studies.

The New England Association of Schools and College, Commission on Institutions of Higher Education addresses institutional effectiveness directly in two standards (Head & Johnson, 2011). However, they go a step beyond Middle States and mention the term "institutional effectiveness" within each of the eleven standards (Head & Johnson). The process is also noted as cyclical.

The Higher Learning Commission (HLC) has five criteria for accreditation and criterion 2 is concerned with institutional effectiveness. The researchers note that HLC provides examples of evidence institutions must use to demonstrate compliance with institutional effectiveness, including, "evidence that an organization's performance matches its stated expectations; effective systems for collecting, analyzing, and using data; feedback loops use for continuous improvement; regular reviews of all academic and administrative units; and adequate support and resources for evaluation and assessment processes" (Head & Johnson, 2011, p. 40). Key words in this criterion are “continuous improvement,” “loop,” and “regular reviews.” These terms indicate the continuous improvement process.

Institutional effectiveness is ingrained in the Northwest Commission on Colleges and Universities mission statement. Standard 4, called Effectiveness and Improvement, embodies expectations for continuous quality improvement methods. Interestingly, suggestions for evidence of this standard are student outcomes driven and include: annual goals and assessments of success in their (students’) accomplishments; students of alumni and former students; studies regarding effectiveness of programs and their graduations; studies that indicate degree of success in placing students; pre-and-post-test comparisons of student knowledge, skills, and abilities; and, surveys of satisfaction—students, alumni, and employees” (Head & Johnson, 2011, p. 42). This observation is in opposition to Brookes and Becket’s (2007) findings. The value of student outcomes in continuous improvement models is important to this dissertation because student success outcomes are being connected to continuous improvement efforts and predictive modeling is the proposed tool to improve the outcomes by modifying the PDSA Cycle.

The Western Association of Schools and Accrediting Commission for Community and Junior Colleges embed continuous improvement expectations in their standards for both senior higher education institutions and community and junior colleges (Head & Johnson, 2011). The commission created a rubric to help institutions evaluate institutional effectiveness on their campus. Head and Johnson explain, “The rubric covers three characteristics of an institutional effectiveness program: program review, planning, and student learning outcomes. The institution can evaluate itself at one of four levels of proficiency: awareness, development, proficiency, or sustainable continuous quality improvement" (2011, p. 44).

Finally, SACS, the commission that originally coined the term "institutional effectiveness" unsurprisingly has quality enhancement principles permeated throughout their process (Head & Johnson, 2011). Head and Johnson go on to discuss three cases applying a common methodology based on SACS standards to demonstrate a transferable process to improve practices that they believe is found in all accreditors expectations.

Community colleges. Skolits and Graybeal (2007) used a mixed-method case study approach to examine institutional effectiveness at a single community college in Tennessee. They note that research on institutional effectiveness in the early 2000s focused on macro-level studies with multiple institutions and was usually focused on 4-year institutions. They sought to understand institutional effectiveness practices at community colleges.

Skolits and Graybeal (2007) found six values and expectations of the college's institutional effectiveness process, including: strategic alignment; resources linked to priorities; assessment and evaluation of priorities at all institutional levels; use of assessment results for continuous improvement; campus wide participation in the institutional effectiveness processes; and, employee responsibility for institutional effectiveness. Interviews with senior campus leaderships confirmed that institutional effectiveness at this institution is consistent with their policies and reflect campus efforts of planning, assessment, and improvement (Skolits & Graybeal, 2007). Three strengths were noted of the process: "the overall utility of the effectiveness process, strategic planning and management, and accuracy of institutional data" (Skolits & Graybeal, 2007,

p. 309). Data and research were consistently cited as integral to the institutional effectiveness process in both administrative and academic leader interviews. While availability of data was not an issue, administrative leaders saw an opportunity for units to improve their analysis of data and their use of data.

Two barriers were found to institutional effectiveness: lack of time and lack of resources (Skolits & Graybeal, 2007). Skoltis and Graybeal explain, "the institution's efforts at collecting data might be reduced in favor of increased support to promote faculty and staff use of existing data" (2007, p. 319). This finding presents an opportunity for college researchers to focus on the quality and use of office outputs, rather than the continued production of new data. In addition, this might lend credence to this study's hypothesis that predicative modeling is an opportunity to put data to use in higher education, instead of producing descriptive datasets that are not actionable.

Sheldon et al. (2008) describe an effectiveness model in higher education which sought to provide a connection between organizational management literature and institutional effectiveness literature in higher education through descriptive analysis and a case study example. This study used a model the University of New England created. With a descriptive case study approach, this study was more useful for model development than providing empirical evidence. Their model of implementation effectiveness considered how to successfully implement and sustain institutional effectiveness in institutions of higher education (Sheldon et al.).

Sheldon et al. (2008) note that coordination, collective use, and team commitment are essential for implementation effectiveness to occur. Additionally, implementation of the model or program is a main reason why institutional effectiveness efforts fail

(Sheldon et al.). Connected to implementation, if faculty and staff believe that institutional effectiveness efforts are primarily motivated by external forces, such as accreditation, they are less likely to be receptive—which can cause issues (Sheldon, et al.). A document review of administrative unit assessment produced nine outcomes themes, including: "quality of student life, quality of institutional leadership, quality of service to university constituents, interdepartmental communication and collaboration, quality of external relationships, a safe and healthy campus, strengthening of institutional image, institutional and fiscal viability, and cost-effectiveness of operations" (Sheldon et al., 2008, p. 23). These observations provide valuable guidance on successful implementation of institutional effectiveness models.

This body of literature exemplifies how continuous improvement has been studied and implemented in higher education to this point. The body of literature indicates that institutions of higher education use continuous improvement processes as their model of quality management. However, as explained in chapter one, this method of improvement has not resulted in changes to student success rates nationally, namely student retention and graduation rates. By modifying the PDSA Cycle to add predictive analytics to the planning stage of the cycle, institutions will have the opportunity to identify at-risk students early. Additionally, other sectors in higher education, such as enrollment management and alumni giving, could benefits from a modified process continuous improvement process with predictive analytics.

Predictive Analytics in Higher Education

Predictive analytics is a young field in higher education. Thus, the body of literature on predictive analytics is small. The majority of studies focus on case study models that were created at individual institutions but lack any explanation of how the model was or was not used at the institution.

Analytics

Analytics are a group of data concepts and tools that are used for data-driven decision making (van Barneveld, Arnold, & Campbell, 2012). The private sector has used analytics for decades to increase profitability, particularly in the field of predicting consumer behavior (Eduventures, 2013). Higher education is a late adopter of this tool. In recent years some institutions of higher education have made investments in analytics because some institutions are demonstrating that analytics can be used to achieve strategic outcomes (Bichsel, 2012). According to Bichsel (2012), “Analytics is the use of data, statistical analysis, and explanatory and predictive models to gain insights and act on complex issues” (p. 6). The insight gained from analytics is not valuable if institutions do not take action with the information gained.

Historically, institutions of higher education have relied on descriptive analytics to reactively look at what happened in the past in relation to student and institutional outcomes. Bichsel’s (2012) study found that institutions are stuck in the data-collection and data-monitoring stages and are not using data for prediction or decision making. Higher education needs to use proactive analytical tools that move data analysis past reporting and into actionable insight (van Barneveld et. al., 2012). Predictive analytics offer the ability to proactively use data to achieve institutional priorities.

Predictive analytics. Predictive analytics are statistical analyses that offer the ability to predict future outcomes by looking for patterns in previous data. The power in predictive analytics is their ability to help “plan for the future by combining data about who, what, where and when to analyze why and how" (Rajni & Malaya, 2015). If higher education leaders started planning for the future with actionable information about their students and institutions it would be possible to design informed strategies to intervene on a host of goals.

There are many goals of predictive analytics. Rajini & Malaya (2015) explain, "The goal of predictive analytics are to produce relevant information, actionable insight, better outcomes, and smarter decisions, and to predict future events by analyzing the volume, veracity, velocity, variety and value of large amounts of data" (p. 25). Some goals of predictive analytics in higher education are to determine which applicants are likely to enroll, which students are likely to be retained and graduate, and which alumni are likely to give (Eduventures, 2013). By predicting these outcomes, institutions are empowered to target interventions and scarce resources at students who need them most.

Baer and Hill Duin (2014) note that analytics is gaining momentum in higher education and that teams on campus are using analytics to assess data, trends and outcomes. They also claim that, "metrics are moving from the level of reporting and analysis to action, in which higher education can make sense of what is going on with students" (Baer & Hill Duin, 2014, p. 32). However, this claim is unsubstantiated by empirical research. Most research on predictive analytics in higher education lacks a connection to action.

Current Use of Predictive Analytics in Higher Education

Predictive analytics in higher education literature focuses on the creation of models related to enrollment prediction, alumni giving, online learning, graduation prediction and retention prediction. Prior to this study, little empirical literature exists that connects the models to intervention; however, most of the literature argues that is what needs to happen with the models.

Enrollment prediction models. Enrollment prediction modeling is important for college budgeting. According to Chen (2008), "the integrated enrollment forecast model is developed to achieve a better understanding of the variables affecting student enrollment and, ultimately, to perform accurate forecasts" (p. 2). By creating accurate models, colleges should be able to use predicted enrollment to create budgets based on expected student headcounts and credit hours. Literature related to enrollment prediction modeling in higher education is limited to model creation and does not address how institutions did or did not use the models for budgeting. Several examples can be cited where colleges created enrollment prediction models, but do not assess whether they were used to predict college budgets and if those predictions were successful (DeLeeuw, 2012; O'Bryant, 1990; Zhang, 2007). Only one case study from the University of Delaware was found that explains the enrollment prediction model and how it was actively used to plan the college's budget (Trusheim & Rylee, 2011). Enrollment prediction modeling literature is limited, but that which does exist does not address if colleges are proactively using the models to plan and act.

Alumni giving models. Skari's (2014) study created a predictive model for community colleges to determine variables influencing alumni giving. Important alumni giving variables were student experience, age, income, and giving patterns to other organizations, which Skari noted as consistent with 4-year alumni giving literature. Skari (2014) explains the model is important because it "narrows the scope of potential donors and allows institutions to prioritize their time and efforts on those alumni most likely to give" (p. 38). The study does not address if institutions have taken a proactive approach with the model and connected it to intervention.

Online learning models. The online learning environment offers a data rich environment to look at student learning and behavior outcomes. Smith, Lange, and Huston (2012) analyzed student information to build a statistical model to forecast student outcomes in online courses at a community college. "Two predictive models were presented showing that these factors [log-in frequency, site engagement, pace, assignment grades, and some non-LMS enrollment factors] can be used to accurately predict the likelihood of course success at any given point in the semester" (Smith, Lange, & Huston, 2012 p. 51). A growing number of programs are being offered partially or totally online. According to the Babson Research Group's Annual Survey of Online Learning (Allen & Seaman, 2011) over six million college students are taking an online course, making up one-third of all students.

Graduation models. Some educational researchers are creating predictive models related to graduation. They have found a host of predictor variables, such as high school GPA, engagement variables from the Community College Survey of Student Engagement, enrollment status, race/ethnicity, and gender, that influence a student's likelihood to graduate from both 2-year and 4-year institutions (Price, 2014; Tim, 2013; Wang, 2009). While some of the articles discuss policy and institutional implications for the use of such models, none discuss how the models have been used at institutions to actually make an impact on a college's graduation rate.

At-risk student retention models. Studies have shown that the first year of a student's higher education life cycle is when they are most at-risk for drop-out (Learning

Slope, 1991). Bevitt, Bladwin, and Calvert (2009) argue that "meeting with absent and underperforming students at the earliest possible opportunity has proved an effective way of promoting dialogue between staff and student who are experience difficulties" (p. 1). Knowing that intervention timing is an important variable in affecting student retention, it is important to consider student retention predictive models as a tool for early intervention.

The 2011 Student Retention Practices at Four-year and Two-year Institutions study conducted by Noel-Levitz asked participating institutions to identify if they use statistical modeling to predict the likelihood of an incoming student persisting to degree completion. Fifty percent of private 4-year schools, 52% of public 4-year schools, and 30% of community colleges identified themselves as using predictive modeling (Noel-Levitz, 2011). Of these institutions, 65% of private 4-year institutions, 59% of public 4-year institutions, and 47% of community colleges rated these models as "very effective" or "somewhat effective." What remains unclear is whether these schools make the connection between a valid and reliable student retention model and success interventions to support those identified students. This study will fill that gap. In addition, this study is six years old; so, this study will be able to look for anything changes in usage that have or have not occurred during this time period. The findings of this study are limited because the sample is not stated and neither is the response rate.

New York University created three logistic regression models to predict student retention at three distinct times during their first semester (Sadler, Cohen, & Kockesen, 1997). The study sample was 2,209 freshmen from Fall 1994 and 1995 first-time cohorts of which 272 did not return the following fall. "Variables were grouped into six general categories describing: (1) family background/individual attributes; (2) pre-college schooling; (3) institution commitment; (4) first-term academic integration; (5) first-term social integration; and (6) first-year finances" (1997, p.1). All three models were effective in identifying high risk students using three first semester cutoff points. The study concluded that use of all three models to identify students at risk at the three different times would allow for an optimum intervention strategy; however, the study does not test intervention strategies on student identified as at-risk by any of the models.

Herzog (2005) identified several variables, including higher school preparation, first-year academic performance, multi-institution enrollment, and financial aid support as predictors of student fall-to-fall retention. Student success intervention was not addressed in this study. While most studies on predictive analytics do not connect the models to intervention, there are examples of institutions that are successfully implementing this model to achieve retention and graduation goals.

Civitas Learning. Civitas Learning is a software system that helps colleges create predictive models, connect them to student success intervention, and assess student success results. Milliron, Malcolm and Kil (2014) shares three case studies of unnamed institutions using Civitas products to identify at-risk students and target them with interventions. The researchers note that a goal of each school's predictive analytics efforts was to "demonstrate that predictive analytics in combination with targeted interventions can improve student outcomes" (Milliron, Malcolm, & Kil, 2014, p. 74). Overall, the three schools saw an average improvement of 3% between test and control groups with a 98% confidence level (Milliron, Malcolm & Kil).

Purdue Course Signals. The Purdue Course Signals project was the first predictive analytics initiative to show positive results by connecting at-risk student predictive models with intervention strategy. Course Signals creates student models for each course a student is enrolled in and indicates for the student a red, yellow, or green signal representing that courses success (Arnold & Pistilli, 2012). The models behind the signal are based on "performance, measured by percentage of points earned in course to date; effort, as defined by interaction with Blackboard Vista, Purdue's LMS, as compared to students' peers; prior academic history, including academic preparation, higher school GPA, and standardized test scores; and, student characteristics, such as residency, age, or credits attempted" (Arnold & Pistilli, 2012, pp. 1-2). Instructors initiate interventions, which may include any or combinations of the following: "posting of a traffic signal indicator on the student's LMS homepage; e-mail messages or reminders; text messages; referral to academic advisor or academic resource centers; or, face to face meetings with the instructor" (Arnold & Pistilli, 2012, p.2). The results of this project from the fall 2007, 2008, and 2009 cohorts indicate that students in Course Signals courses are retained at statistically significant higher rates than students with no course signals courses (Arnold & Pistilli). In addition, students who took two or more Course Signals courses were retained at higher rates than students in one or no Course Signals courses (Arnold & Pistilli).

Interviews with campus administrators about the Course Signals project indicate that administrators believe early and frequent feedback to students is important to student success (Arnold, Tanes, & King, 2010). The administrators felt that Course Signals the achievement of strategic university goals (Arnold, Tanes, & King). However, concern was expressed over “the resources required to maintain and implement Signals technology and whether or not it was possible to scale Signals use across a large campus” (Arnold, Tanes, & King, 2010, p. 29). This concern will be important to research in this dissertation.

Marist College. Marist College leads the Open Academic Analytics Initiative (OAAI) which is an open-sourced predictive analytics project that used student data to create at-risk models and connect at-risk students with intervention by their professors. Marist’s at-risk student models were built using student data across institutions using the same statistically significant variables that John Campbell used, which were demographic, aptitude, and course management system data and deployed at two community college (Bainbridge, Melitski, Lauria, Jayaprakash, & Baron, 2015). Their models assessed a student’s likelihood of course drop out at three points in the semester 25%, 50%, and 75% complete. The models were found to be accurate (Lauria et al., 2013). Instructors were notified of students’ predictive dropout rates and two intervention strategies were used.

Awareness messaging was the first intervention used. Awareness messaging “entails the instructor sending a message to the “at-risk” student noting their concern over the student’s academic performance and then suggesting specific steps the student should take to improve (e.g., meet with a tutor, attend a student group session, etc.)” (Lauria et al., 2013, p. 152). The second intervention is a standardized message called “Online Academic Support Environment” which invites students to join an online support systems with instructional materials available to them (Lauria et al.). The authors note that messages are standards across instructors and become more serious in tone with each additional message sent. The findings from this pilot were positive.

Using a one-way ANOVA to compare average course grades between the treatment and control groups, the researchers found statistically significant differences (Lauria et al., 2013). The results suggest that interventions benefitted academically at-risk students the most. The results of this study also provide support that models can be built and ported across institutions using the same at-risk student variables (Lauria et al., 2013).

Challenges of Predictive Analytics in Higher Education

Despite evidence that predictive analytics can be used to improve outcomes in higher education, campus information technology and institutional research professionals believe that their campuses do not use analytics to their fullest potential (Bichsel, 2012). The purpose of Bichsel's (2012) study (for the Educause Center for Applied Research) was to "gauge the current state of analytics in higher education" (p. 5). Through a surveyed sample of Educause institutions and the Association of Institutional Research (AIR) professionals, as well as follow-up focus groups, Bichsel found that while 69% of respondents felt that analytics was a major priority for some departments on their campus "in most cases, respondents were using data at a level below the threshold identified in the Educause definition of analytics—this is, using data proactively or to make predictions" (p. 10). Affordability of analytics was cited as a practitioner concern; however, "several focus group members remarked that when senior leadership agrees that analytics is a priority and part of the strategic plan, then cost becomes less of an issue" (Bichsel, 2012, p. 14). Another important finding from Bichsel's study is that an institution's culture was cited as a barrier to the successful use of analytics in higher education. It was believed by participants that administrators, faculty, and staff fear the use of data, mistrust data, and do not know how to use to data to make decisions. This survey was focused on analytics broadly speaking. This dissertation's survey focus is different, as it is concerned with predictive analytics specifically. In addition, Bichsel's study is 5 years old. The emerging nature of this field requires more frequent study.

In a League for Innovation survey of 1,049 college and campus CEOs with a 26.7% response rate, 76.9% of respondents indicated they would be adapting performance-based funding models (de los Santos & Milliron, 2015). In addition, 90% of respondents say they would be responding to increasing completion-centric expectations from accreditors (de los Santos & Milliron). These findings support this dissertations argument that colleges are under increased accountability expectations. Interestingly, respondents to this survey also indicated that over the next 2-years 97.5% of schools would use data to guide change efforts, 98.2% would use data to better understand and serve students, and 96.4% will use data in more sophisticated ways to respond to increasing calls for accountability (de los Santos & Milliron). If so many college CEOs recognize that accountability expectations are increasing and that data can help meet those expectations, it remains unclear why more institutions are not successfully using data to meet these performance demands.

Methodological Review

The literature reviewed in this dissertation on continuous improvement is primarily case studies at individual institutions (Brown & Marshall, 2008; Edward, McKinney, & Tuttle, 2006; Jenicke, Holmes & Pisani, 2013; Jenkins, 2007; Lillis, 2012), with a couple examples of content analysis (Brooks & Becket, 2007; Pratasvitskaya & Stensaker, 2010) and surveys (Garcia-Bernal & Ramirez-Alexson, 2015; Skolits & Graybeal, 2007). Methodological issues are cited as a challenge to assessing continuous improvement impact (Stensaker, 2007), which has led to the literature becoming case study focused. Havey and Newton explain, "Establishing definitive causal links and isolating their effects from other factors is a difficult task" (2004, p. 59). In addition, the regional accreditors encourage institutions to develop their own institutional effectiveness models, which makes meta-analysis or large scale comparison difficult. However, without examples of large scale impact, like we see in business and health care literature, quality improvement in higher education runs the risk of becoming obsolete and a bureaucratic requirement.

The literature reviewed on predictive analytics was primarily case studies of quantitative predictive models created at individual institutions for enrollment modeling (DeLeeuw, 2012; O'Bryant, 1990; Trusheim & Rylee, 2011; Zhang, 2007), alumni giving (Skari, 2014), online learning (Smith, Lange, & Huston, 2012), graduation prediction (Price, 2014; Tim, 2013; Wang, 2009), and retention prediction (Sadler, Cohen, & Kockesen, 1997). Almost all these case studies fail to address how an institution used the models to improve the subject the models are targeting.

There are case study examples of institutions that are using predictive analytics in combination with success interventions (Arnold & Pistilli, 2012; Bainbridge, Melitski, Lauria, Jayaprakash, & Baron, 2015; Milliron, Malcolm, & Kil, 2014). These case studies provide support for the thesis of this dissertation: that predictive analytics in combination with intervention can improve student success outcomes.

Substantive gaps. As noted in Skolits and Graybeal's (2007) study data and research were consistently cited as integral to the institutional effectiveness process in both administrative and academic leader interviews. That a finding of this study was the opportunity for units to improve their analysis of data and their use of data is important to this dissertation because predictive modeling may be the tool that improves the outcomes portion of continuous improvement models in higher education.

The surveys conducted by Noel Levitz (2011) and Bichsel (2012) provide insight into the use of predictive analytics in higher education and some of the challenges and opportunities that exist. Four and 5 years have occurred since these surveys were conducted, respectively. The emerging field of predictive analytics is changing and warrants further investigation into how predictive analytics is being used today in higher education.

Chapter Summary

This chapter provides an analysis of continuous improvement and predictive analytics literature in higher education. Continuous improvement in higher education gained traction through regional accrediting bodies that created their own quality improvement models and made the process a requirement for institutional reviews.

The empirical literature reviewed was mostly case studies of specific institutions of higher education. This was surprising since each college make their own continuous improvement model within the boundaries their regional accreditor has set. Thus, it is difficult to compare institutional effectiveness models across institutions. Interviews and surveys were another source of empirical data on this topic and offer the best comparative opportunities.

Most of the literature reviewed provides little evidence that the continuous improvement models in higher education are impacting student success. Data shows that student graduation rates are not improving in any sector. If increasing the number of students completing degrees and credentials is the ultimate goal of higher education, and continuous improvement models are meant to improve processes to get the institution towards the ultimate goal, further research must explore the relationship between continuous improvement processes and educational goals.

Chapter 3: Research Design Methodology

Introduction

As explained in Chapter 1, the federal government and state governments are calling for increased student success outcomes from institutions of higher education in the form of performance based funding because minimal gains have been made to student retention and graduation rates (Digest of Education Statistics, 2014; Schnieder 2010). Student debt has crept to more than a trillion dollars, and research shows students who do not complete their degrees are most likely to default on their student loans (Berman, 2016; National Center for Education Statistics, 2009). Higher education leadership must look to innovative approaches to achieve student completion goals. Modifying the existing continuous improvement process with predictive analytics provides the ability to identify at-risk students before they show signs of academic difficulty.

This study adds to an emerging body of literature on predictive analytics by answering the following primary research questions:

1. Are colleges and universities using predictive analytics to identify at-risk students and provide student success interventions?
2. How are predictive analytics being used on college campuses?
    a. How are they used with student success interventions on college campuses?
3. What strategies are being used to facilitate or prohibit the use of predictive analytics with student success intervention?

This study also looks for similarities and differences that might exist in how 2-year and 4-year, public and private institutions are using predictive analytics. To answer these research questions a survey was sent to a sample of institutional research and effectiveness personnel at 2-year and 4-year, private and public colleges and universities across the United States.

Research Context

This study took place in the United States during the spring of 2017. Colleges and universities across the United States were included in the sample. Both 2-year and 4-year post-secondary institutions that are public and private were included. According to the U.S. Department of Education's most recent reporting year, there were 1,700 degree granting 2-year colleges and 3,026 degree granting 4-year colleges in the United States (National Center for Education Statistics, 2016). Institutions in this county must be accredited to receive federal funding and be considered in the population of this study.

The Higher Education Opportunity Act of 2008 reauthorizing the Higher Education Act of 1965 requires colleges and universities to obtain and maintain accreditation by an accreditor recognized by the Council for Higher Education Accreditation to receive Title IV financial aid funds, which are student loans and grants provided via the federal government. There is also data compliance regulations associated with Title IV. Institutional research and effectiveness professionals on college campuses are primarily responsible for collecting and submitting this data.

Institutional researchers are members of the college community with responsibility for reporting compliance, data analysis, and research. They are the individuals with expertise related to student data and outcomes reporting. The model presented in this dissertation would be led or collaborated with institutional research personnel on college campuses. Institutional researchers are the staff with predictive analytics expertise and would have the best understanding of the state of predictive analytics on a college campus. Institutional research is a function of institutional effectiveness. Many college campuses have institutional effectiveness offices that include the institutional research function.

The literature review of this study showed that a gap exists in our understanding of predictive analytics on college campuses. As this expanding subfield in institutional research/effectiveness grows, it is important to understand, from those responsible for implementing and designing predictive analytics, what the current state of predictive analytics on college and university campuses is. In order to obtain this information, a sample of institutional research personnel of all accredited post-secondary institutions across the United States was surveyed.

Research Participants

The participants for this study were a sample of individuals responsible for institutional research and effectiveness function at their institution. These individuals are the most likely post-secondary staff members to be involved with predictive analytics on a college campus and will have the most thorough understanding of how they are or are not being used.

Sample frame. To obtain the sample of institutional researchers a file of colleges and universities that receive federal funds was obtained. This file is publically available on the National Center for Education Statistics (NCES) website. According to the Higher Education Act of 1965, all institutions that receive title IV funds are mandated to complete Integrated Postsecondary Education Data System (IPEDS) surveys (Department of Education, 2016). These surveys are analyzed by NCES and made publically available on the IPEDS website.

The Directory Information file contains all post-secondary institutions in the United States that are submitted to IPEDS. This file is created from the Institutional Characteristics survey. The file was obtained by going to the IPEDS data center website, selecting complete data file, the year 2015 (most recent year available), all surveys, and then selected the Excel file version of the Directory Information file. A directory of data fields is available for this file following the same steps to understand the coding of file variable fields. This file was used to identify the personnel at a random sample of institutions the survey was administered to.

The following data fields were used from Directory of Information file for analysis of the institutions in the study. The fields are: UNITID (institutional identification number to join files), INSTNM (institution name), STABBR (State of college, i.e., location), SECTOR (identifies 2-year or 4-year, public or private status; only selections 1, 2, 4, 5, 7, and 8 were used to filter out pro-profit colleges and administrative offices), ICLEVEL (identifies classification of whether an institution’s programs are 4-year or higher (4 year), 2-but-less-than 4-year (2 year), or less than 2-year), CYACTIVE (whether the school was active/open in the current year using the filter 1), and INSTSIZE (the 12 month induplication enrollment of the institution.

Random sample. The original file contained 7,647 post-secondary institutions. After sorting out the selections outlined above, for-profit colleges, administrative offices, and closed institutions, 3,978 institutions remained. Using the Microsoft Excel =Rand()

function, each institution was assigned a random number. The random number was sorted from lowest to highest. To obtain a 95% confidence level with a 3% margin of error, the sample size of the survey was calculated to be 842. To achieve a response rate of 30% 2,806 institutions needed to be sent the survey. Therefore 2,806 institutions made up the sample of this study and the first 2,806 institutions in the random number sorted file were selected.

The website for each institution was searched to find the name and e-mail address of the person responsible for institutional research. Key terms to search for were: “institutional research,” “institutional effectiveness,” “data and analytics,” and, “coordinator, director, dean, or vice-president.” If a name was found without an e-mail address, an attempt was made to contact that person. If no name and e-mail address could be found that school was replaced by the next one in the random sample file and a new individual was looked up. This process was followed until the entire random sample had been searched. The researcher was not able to obtain the e-mail addresses of all the random sample institutional research personnel. She then continued to replace the schools with the rest of the population. A total of 2,237 institutional research and effectiveness personnel e-mail addresses were found as unique institutions.

Instruments Used in Data Collection

The survey instrument used in this study was developed by the researcher. The survey instrument, see Appendix A, begins with an informed consent question that is followed by two screening questions to determine if the correct individual at the institution was identified. Those questions ask if the person has responsibility or high level experience with institutional research at their institution. If they did not, the survey ended. If they did, question 2 asked if they are using predictive analytics at their institution. If yes, respondents progressed to section A of the survey. Section A of the survey asked questions about what led to the use of predictive analytics at their institution and for what institutional purposes predictive analytics are being used. These questions are aligned with research questions 1, 2, and 3. If the respondents answered they do not currently use predictive analytics, they progressed to section C of the survey. Section C asks questions about interest in using predictive analytics at their institutions and what it would take to start using them. These questions are aligned with research questions 1, 2, and 3. Section B of the survey is specific for respondents that indicated predictive analytics are being use to target at-risk students to improve their success outcomes in section A, question 7. The questions in section B are related to the types of intervention the college is using to target at-risk students. These questions are aligned with research questions 2 and 2-A. The following chart outlines the sections of the survey, the questions within the section, and the research question(s) the survey question is aligned with.

The survey was not pilot tested in order to preserve as many institutional researchers for the study as possible.

Table 3.1

Research Question Survey Alignment

Survey Section and Question Number	**Survey Question**	**Research Question Alignment**
A.1	How long has your institution been using predictive analytics?	One
A.2	What factors contributed to the use of predictive analytics on your campus?	Three
A.3	Which individuals were initially supportive of using predictive analytics on your campus?	Three
A.4	What staff and/or faculty, if any, are currently supportive of the use of predictive analytics on your campus?	Three
A.5	Does your institution use predictive analytics for enrollment management purposes?	Two
A.6	Does your institution use predictive analytics for advancement purposes?	Two
A.7	Does your institution use predictive analytics to target student success outcomes, such as Retention and/or Graduation?	One and Two-A
B.1	Does your college provide a type of intervention (ex. Advising, recommendations to help center, etc.) to students that are identified as at-risk using predictive analytics?	Two-A
B.1	What intervention(s) does your college provide to students that are identified as at-risk using predictive analytics? (Select all that apply)	Two-A
B.4	Why doesn't your college connect intervention to the at-risk student predictive model?	Two
C.1	To the best of your knowledge has your institution considered using predictive analytics on your campus?	One
C.2	What has prevented your institution from using predictive analytics on your campus?	Three
C.3	Do you believe your institution will begin using predictive analytics in the next:	One
C.4	What staff and/or faculty support would be required for predictive analytics to be used on your campus?	Three
C.5	What staff and/or faculty, if any, are currently supportive of the use of predictive analytics on your campus?	Three
C.6	If your institution were to begin using predictive analytics, what functions do you believe it would use them for?	Two

Procedure

First, for recruitment of participants in this study the sample was obtained and the school's institutional researchers email addresses were located via their website or a phone call to the institution. The survey was designed using Qualtrics online software. Institutional Review Board approval was obtained by the St. John Fisher College Institutional Review Board. Next, the survey was sent to the sample from the researcher's St. John Fisher College e-mail address. Each participant was required to answer an informed consent question, based on the St. John Fisher College Institutional Review Board guidelines, before entering the survey. Three reminder e-mails were sent. A message indicating the survey was closing was sent on day 17. All survey responses were downloaded at the close of the survey into a password protected Excel file that was kept on the researcher's computer. Survey response data was connected to the sample file intuitional data. The respondent's e-mail and institution was deleted from the file to maintain confidentiality. At this time data analysis took place using SPSS statistical software.

Procedures for Data Analysis

Once the survey closed, data was downloaded from the online Qualtrics database. Survey respondents were matched to the original file containing information about each school in the sample. The data was exported to SPSS statistical software for analysis.

The survey response rate was calculated by dividing total responses by the total sample. Descriptive charts were created to demonstrate who the responding institutions were. The charts show the 2-year/4-year, public/private response averages. They also show the average enrollment of the respondent schools. Cross tab charts show the average response for each survey question and the total responses. Chi-square tests were used to identify statistical differences between 2-year and 4-year institutions and public versus private institutions compared to the population.

Summary

This study asked institutional research and effectiveness personnel across the United States the status of predictive analytics at their institution. The personnel e-mail address was obtain from their institutions website. It asked them questions regarding how predictive analytics are or are not being used on their campus. Campuses not using predictive analytics were asked about what is prohibiting their use. Campuses using predictive analytics and connecting them to student success interventions were asked what interventions they were using to try to impact at-risk student success.

Chapter 4: Results

Research Questions

This study sought to answer the following research questions:

1. Are colleges and universities using predictive analytics to identify at-risk students and provide student success interventions?
2. How are predictive analytics being used with student success interventions on college campuses?
3. What strategies are being used to facilitate or prohibit the use of predictive analytics with student success intervention?

This study also addresses the impact of institution size and institution type, 2-year versus 4-year, on the use of predictive analytics in higher education.

Data Analysis and Findings

Respondents. The Predictive Analytics in Higher Education survey was sent to 2,237 institutional research professionals in the United States. A total of 350 completed surveys were received resulting in a 16% response rate. Table 4.1 shows the results by institution type compared to the population.

Table 4.1

Results by Institution Type

	% Observed	*(n) Observed*	*% Expected*	*(n) Expected*
Private, 2-year	.008	*3*	*.07*	24
Private, 4-year or above	.43	151	.43	150
Public, 2-year	.27	97	.32	112
Public, 4-year	.28	99	.18	63

Note. $\chi^2 = 41.449$
*p < .001

Private not-for-profit, 4-year institutions were proportionally represented in this study. Public, 2-year or less institutions are slightly underrepresented. Public, 4-year institutions were over represented in this study. Finally, private not-for profit, 2-year institutions were not well represented in this study.

Respondent results by institution size are demonstrated in Table 4.2 below.

Table 4.2

Results by Institution Size

	% Observed	*(n) Observed*	*% Expected*	*(n) Expected*
Under 1,000	.12	41	.38	133
1,000-4,999	.46	160	.36	126
5,000-9,999	.19	67	.12	42
10,000-19,999	.15	54	.08	28
20,000+	.08	28	.05	17.5

Note. $\chi^2 = 118.138$
*p < .001

Institutions with a size of 1,000-4,999 students were overrepresented in this study, as were institutions with 10,000-19,999 students. Institutions with 20,000 or more students were well represented in this study. Institutions with 5,000-9,999 students were slightly overrepresented in this study. Small institutions with fewer than 1,000 were underrepresented in this study.

Results. Of the 350 respondents to this survey, 61% of them use predictive analytics on their campus and 39% of them do not. Respondents were categorized into four implementation categories: never considered implementing predictive analytics (NCIPA), intention to use predictive analytics (IPA), partial implementation of predictive analytics (PIPA), and full implementation of predictive analytics (FIPA). Campuses that answered "No" to question C1 indicated their campus had not considered using predictive analytics and were categorized as NCIPA. Campuses that answered "Yes" to C1 (Appendix A) were subsequently categorized as IPA. This dissertation argues that predictive analytics needs to be connected to intervention to make change. Thus, campuses using predictive analytics to identify at-risk students and for other purposes, but are not connecting intervention to those identified at-risk students, were considered partial implementers of predictive analytics in this study. These campuses answered "No" to question B1 (Appendix A). Institutions that answered "Yes" to question B1 were FIPA because they connect intervention to students identified as at-risk. Using these categories, implementation levels were compared by institution size and institution sector.

Institution size. Figure 4.1 shows predictive analytics implementation categories by institution size.

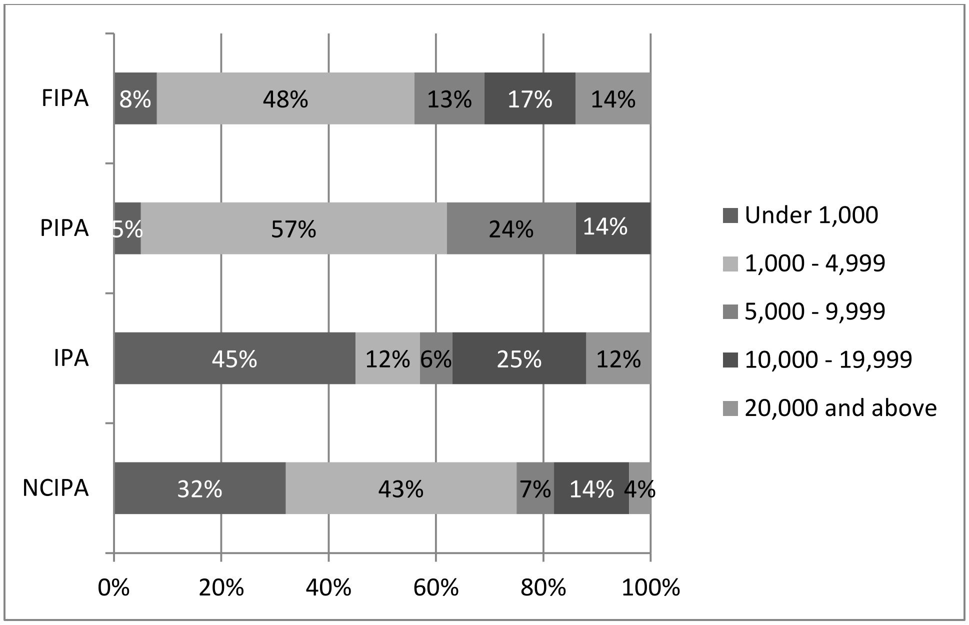

Figure 4.1. Implementation by Institution Size
NCIPA = Never Considered Implementing Predictive Analytics
IPA = Intention to Use Predictive Analytics
PIPA = Partial Implementation of Predictive Analytics
FIPA = Full Implementation of Predictive Analytics

Figure 4.1 shows that smaller institutions with fewer than 1,000 students and 1,000-4,000 students are most likely not to have considered using predictive analytics at a combined 75%. In addition, 57% of institutions with fewer than 1,000 students and 10,000-19,999 students are not using predictive analytics but have intentions of using them.

Figure 4.1 shows that institutions with 1,000-4,999 students are most likely to have partial implementation of predictive analytics. Institutions with 5,000-9,999 students are second likely to have partial implementation at 24%. Finally, institutions at full implementation of predictive analytics are most likely to have 1,000-4,999 students at 48%. Institutions with 10,000-19,999 or more account for 31% of institutions connecting intervention to at-risk student predictive models.

Table 4.3 displays the results of a cross tabulation chi-square test showing a significant association between predictive analytics implementation levels and institution size.

Table 4.3

Predictive Analytics Implementation Level by Institution Size

	Under 1,000	1,000-4,999	5,000-9,999	10,000-19,999	20,000+
NCIPA	22%	8%	7%	7%	4%
IPA	32%	31%	40%	24%	25%
PIPA	2%	8%	7%	6%	0%
FIPA	44%	54%	46%	63%	71%

Note. $\chi^2 = 23.406$
*p < .05

Institution sector. Figure 4.2 shows predictive analytics implementation categories by institution sector. Figure 4.2 demonstrates that public, 2-year institutions (50%) and private, 4-year institutions (39%) are the most likely to indicate no consideration of predictive analytics on their campus.

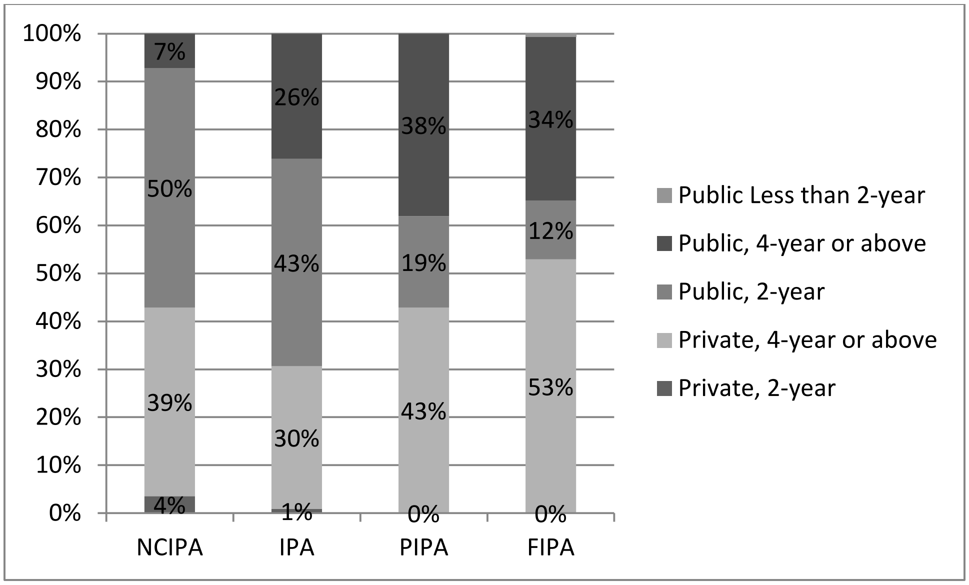

Figure 4.2. Implementation by Institution Sector
NCIPA = Never Considered Implementing Predictive Analytics
IPA = Intention to Use Predictive Analytics
PIPA = Partial Implementation of Predictive Analytics
FIPA = Full Implementation of Predictive Analytics

According to Figure 4.2, 43% of public, 2-year institutions have considered using predictive analytics, but are not currently doing so. Fifty-six percent of 4-year institutions, both private (30%) and public (26%) have considered using predictive analytics. Four-year institutions predominately have partial implementation of predictive analytics at 81%, respectively. Nineteen percent of 2-year institutions have partial implementation of predictive analytics. Figure 4.2 also shows that 4-year institutions are the most likely to have full implementation of predictive analytics in higher education at 87%. Fifty-three percent of private, 4-year institutions and 34% of public, 4-year institutions are using predictive analytics to identify at-risk students and connect those students to success intervention. Thirteen percent of public and private 2-year institutions indicated full implementation of predictive analytics.

Table 4.4 displays the results of a cross tabulation Chi-Square test showing a significant association between predictive analytics implementation levels and institution sector.

Table 4.4

Predictive Analytics Implementation Level by Sector

	Private, 2-year	Private, 4-year	Public, 2-year	Public, 4-year
NCIPA	33%	7%	14%	38%
IPA	33%	22%	49%	18%
PIPA	0%	6%	4%	5%
FIPA	33%	65%	32%	38%

Note. $\chi^2 = 40.895$
*p < .05

The results of each survey question are summarized by each section of the survey instrument (Appendix A). Section A comprises questions about how institutions are using predictive analytics. Section B contains questions for institutions using predictive analytics to identify at-risk students and connect them to success interventions. Section C comprises questions for institutions that are not using predictive analytics on their campus.

Section C-no predictive analytics. Thirty-nine percent of respondents are not using predictive analytics on their campuses. Table 4.5 through 4.19 show response counts and percentages for Section C of the survey.

Table 4.5

To the Best of your Knowledge has your Institution Considered Using Predictive Analytics on your Campus?

Answer	Count	Percentage
No	28	20%
Yes	111	80%

Of the institutions not using predictive analytics, Table 4.5 demonstrates that 80% have considered using predictive analytics and 20% have not.

Table 4.6

What has Prevented your Institution from using Predictive Analytics on your Campus? (select all that apply)

Answer	Count	Percentage
Budgetary investment from grant award	5	2%
Budgetary investment from institution	95	30%
Concern over profiling students using predictive variables	13	4%
Interest by the institutional research/effectiveness staff	14	4%
Pressure to influence student success outcomes	3	1%
Senior leadership support	36	12%
Staffing investment from institution	85	27%
Technology investment by institution	62	20%

Thirty percent of institutions report budgetary investment from the institution as the main reason keeping their institution from using predictive analytics. Staffing investment is second at 27% and technology investment is third at 20%. In the open ended comments, small institution size and not collecting the data needed were cited as reasons preventing the use of predictive analytics.

Table 4.7

Do you Believe your Institution will Begin Using Predictive Analytics in the Next:

Answer	Count	Percentage
1-2 years	49	37%
3-4 years	62	46%
5+ years	23	17%

Most institutions not using predictive analytics believe their institution will begin using predictive analytics in the next 3-4 years at 46% or as early as 1-2 years at 37%.

Table 4.8

What Staff and/or Faculty Support would be Required for Predictive Analytics to be Used on your Campus? (select all that apply)

Answer	Count	Percentage
Academic Leadership	106	19%
Advancement Leadership	15	3%
Chief Financial Officer	63	11%
Enrollment Management Leadership	71	13%
Full-time Faculty	34	6%
Information Technology personnel	73	13%
Institutional Research/Effectiveness personnel	106	19%
Part-time Faculty	9	2%
President	91	16%

Academic leadership (19%), institutional research/effectiveness personnel (19%) and the college president (16%) are reportedly the most important staff support needed to begin using predictive analytics on college campuses.

Table 4.9

What Staff and/or Faculty, if any, are Currently Supportive of the use of Predictive Analytics on your Campus? (select all that apply)

Answer	Count	Percentage
Academic Leadership	65	17%
Advancement Leadership	13	3%
Chief Financial Officer	21	5%
Enrollment Management Leadership	69	18%
Full-time Faculty	14	4%
Information Technology personnel	31	8%
Institutional Research/Effectiveness personnel	112	29%
Part-time Faculty	7	2%
President	50	13%

Table 4.9 shows that Institutional Effectiveness Personnel are currently the most supportive stuff/faculty group supportive of using predictive analytics on college campuses. Enrollment management leadership is second at 18% followed by academic leadership at 17%.

Table 4.10

If your Institution were to Begin using Predictive Analytics, what Functions do you Believe it would use Them For? (select all that apply)

Answer	Count	Percentage
Enrollment management: admissions, marketing, and/or registration	114	21%
Retention/Graduation: Identifying at-risk face-to-face students	262	49%
Identifying at-risk online (remote) students	131	24%
Advancement: gift planning and/or event planning	28	5%

A total of 73% of respondents not currently using predictive analytics say identifying at-risk face-to-face students or remote students are the most likely functions predictive analytics would serve.

Section A-using predictive analytics. Section A of the survey asked questions about the use of predictive analytics on campuses using the tool.

Table 4.11

How Long has your Institution been using Predictive Analytics?

Answer	Count	Percentage
0-2 years	71	33%
3-4 years	57	27%
5+ years	85	40%

Institutions using predictive analytics have used them for varying amounts of time. Thirty three percent report using them for 0-2 years, 27% report 3-4 years and 40% report 5+ years of use.

Table 4.12

What Factors Contributed to the use of Predictive Analytics on your Campus? (select all that apply)

Answer	Count	Percentage
Budgetary investment from grant award	13	2%
Budgetary investment from institution	74	11%
External accrediting agency recommendations	13	2%
Interest by the institutional research/effectiveness staff	161	25%
Pressure to influence student success outcomes	124	19%
Senior leadership support	141	22%
Staffing investment from institution	58	9%
Technology investment by institution	61	9%

Twenty-five percent of respondents rated interest by institutional research/effectiveness staff as the strongest factor that contributed to the use of predictive analytics on their campus. Senior leadership support was the second factor cited contributing to predictive analytics use at 22%. Finally, pressure to influence student success outcomes was the third factor at 19%. This question aligns with research questions three, what factors contribute to the use of predictive analytics on college campuses. Budgetary investment (2%), external accrediting agency recommendations

(2%), staffing investment (9%), and technology investment (9%) had the lowest contribution to the use of predictive analytics.

Table 4.13

Which Individuals were Initially Supportive of using Predictive Analytics on your Campus? (select all that apply)

Answer	Count	Percentage
Academic Leadership	148	21%
Advancement Leadership	20	3%
Chief Financial Officer	75	11%
Enrollment Management Leadership	128	18%
Full-time Faculty	18	3%
Information Technology personnel	36	5%
Institutional Research/Effectiveness personnel	178	25%
President	102	14%

Institutional research/effectiveness personnel were initially most likely to be supportive of using predictive analytics at 25%. Academic leadership were second at 21%. Finally, enrollment management leadership were the third most supportive at 18%. These individuals are also important to research question 3, as it is important to know what people it takes to implement this model.

Table 4.14

What Staff and/or Faculty, if any, are Currently Supportive of the use of Predictive Analytics on your Campus? (select all that apply)

Answer	Count	Percentage
Academic Leadership	174	18%
Advancement Leadership	45	5%
Chief Financial Officer	112	12%
Enrollment Management Leadership	156	16%
Full-time Faculty	58	6%
Information Technology personnel	69	7%
Institutional Research/Effectiveness personnel	194	20%
President	141	15%

Asked which staff and/or faculty are currently supportive of predictive analytics use on their campus, institutional research and effectiveness personnel are the highest at 20%; a drop of 5 percentage points occurred between initial support and current support for these personnel. Academic leadership are the second most supportive of predictive analytics, followed by the college president.

Table 4.15

Does your Institution use Predictive Analytics for Enrollment Management Purposes? (Select all that apply)

Answer	Count	Percentage
No	30	11%
No, but are planning to add predictive analytics for enrollment management in the next year	20	7%
Yes, admissions	128	45%
Yes, marketing	33	12%
Yes, registration	73	26%

Eighty-two percent of colleges using predictive analytics are using them for enrollment management purposes. Admissions accounts for the majority, 45%, of enrollment management use.

Table 4.16

Does your Institution use Predictive Analytics for Advancement Purposes? (select all that apply)

Answer	Count	Percentage
No	148	77%
No, but we are planning to add predictive analytics for advancement in the next year	16	8%
Yes, event planning	5	3%
Yes, gift giving	24	12%

Fifteen percent of colleges are using predictive analytics for advancement purposes. Eight percent of colleges indicate intent to use them for advancement purposes in the next year.

Table 4.17

Does your Institution use Predictive Analytics to Target Student Success Outcomes, such as Retention and/or Graduation? (select all that apply)

Answer	Count	Percentage
No	18	5%
No, but we are planning to add predictive analytics to target student success outcomes in the next year	24	7%
Yes, to assist with student advising	66	18%
Yes, to provide course success predictions	54	15%
Yes, to identify at-risk face-to-face students	157	43%
Yes, to identify at-risk online (remote) students	43	12%

Eighty-eight percent of campuses that use predictive analytics use them to target student success outcomes. Fifty-five percent use predictive analytics to identify at-risk face-to-face or remote students, which answers research question one of this study.

Section B-connecting to intervention. Section B of the survey asked respondents that are using predictive analytics to target student success outcomes if they are connecting the models to intervention. The following tables show the results of Section B.

Table 4.18

Does your College Provide a Type of Intervention (ex. Advising, recommendations to help center, etc.) to Students who are Identified as At-Risk using Predictive Analytics?

Answer	Count	Percentage
No	21	13%
Yes	138	87%

Eighty-seven percent of institutions using predictive analytics to target student success outcomes indicate they are connecting the analytics to intervention. Research question two asked: How are predictive analytics being used with student success interventions on college campuses? The answers to this question indicate that most campuses using predictive analytics to identify at-risk students are connecting those students to intervention. The next question answers what interventions they are being connected to.

Table 4.19

What Intervention(s) does your College Provide to Students who are Identified as At-Risk using Predictive Analytics? - Selected Choice

Answer	Count	Percentage
Meeting with academic advisor	124	36%
Meeting with instructor	39	11%
Placement in or referral to a specific program for at-risk students	51	15%
Referral to academic center, such as Math, Writing, or Science	103	30%
Referral to online academic resources	31	9%

When asked what interventions their college provides at-risk students identified using predictive analytics, meeting with an academic advisor rates the highest at 36%, followed by referral to an academic center at 30% and placement in or referral to a specific program for at-risk students at 15%.

Summary of Results

Sixty-one percent of colleges are using predictive analytics. Of those using predictive analytics, the majority of these colleges have between 1,000-4,999 students. Of the colleges that have never considered using predictive analytics, 75% of them have 4,999 students or less.

Public, 2-year institutions are the least likely to be using predictive analytics or to have considered using them. Private, 4-year institutions are the most likely to have partial implementation and full implantation of predictive analytics. Overall, public and private 4-year institutions are the most likely to have full implementation of predictive analytics.

Campuses without predictive analytics believe that academic leadership and institutional research/effectiveness personnel are the most important people to adopting predictive analytics. This is consistent with the responses that predictive analytics implementers said were important to their adoption.

Sixty-seven percent of predictive analytics campuses have been using predictive analytics for 3 or more years. Interest by institutional research/effectiveness staff, senior leadership support, and pressure to influence student success outcomes were the factors most likely to encourage use of predictive analytics.

Finally, campuses using predictive analytics are likely to be using them to target at-risk students and to connect them to student success intervention. The most likely interventions they connect them to are academic advisors, academic centers, and referral to a specific at-risk student program.

Chapter 5: Discussion

Introduction

Predictive analytics offer the higher education community a tool to increase student completion rates. Their ability to precisely target desired outcomes by using previous behaviors and interventions make predictive analytics the most proactive power tool education professionals have. Predictive analytics in higher education is a young field, growing in interest over the last decade. Increasing student success outcomes, which the accountability climate mandates must happen, is only the beginning of what predictive analytics can do to help institutions of higher education accomplish goals. As explained in Chapter 1, student success outcomes have not increased despite significant investment by the federal government and colleges. If predictive analytics can be made an integral part of the college strategic planning process, as seen in Figure 1.3, then colleges and universities will be able to increase student success outcomes.

Implications of Findings

The results of this study show that three-fifths of United States colleges and universities are using predictive analytics. Small institutions are the least likely to have considered using them. Institutions with the most robust use of predictive analytics have 1,000-4,999 and 10,000 or more students and are almost exclusively 4-year institutions.

Respondents using predictive analytics and not using predictive analytics differ on the factors that facilitated and are prohibiting the use of predictive analytics on their campus. Where non-users say that budgetary, staffing and technology investments are keeping them from using predictive analytics, adopters say that interest from institutions effectiveness personnel, senior leadership support, and pressure to increase student success outcomes facilitated the adoption. This might be attributed to the institutional size difference between adoptees and non-adopters, as smaller institutions financial resources may be constrained.

Advancement. Of those using predictive analytics, very few are using them for advancement purposes. This is a lost opportunity because predictive analytics can be used to identify which donors are most likely to donate and how much they are likely to donate. This could allow advancement personnel to target their time on the most likely donors. In addition, models could be developed to determine what types of events are likely to garner the most dollars and where the most likely donors make their commitments. Healthy endowments and gifts to institutions are important for financial stability. If potential donors could be given a donation score that accurately predicts their likelihood of giving and the amount they would give, why wouldn't institutions use these models to focus time and resources?

Enrollment management. Four-fifths of institutions using predictive analytics are using them for enrollment management. Admission models are the most common type of enrollment management predictive modeling being done. It stands to reasons selective institutions are using predictive models to identify which students are most likely to be academically successful. Community colleges are usually open admission and admit students with a high school diploma or a high school equivalent degree. Community colleges could create admission models, likely using at-risk student variables, which could give admissions counselors and advisors insight into a student's strengths and challenges prior to beginning coursework. While these models would not be used to determine admission status, there is opportunity to put at-risk students in coursework they are most likely to be successful in early.

A quarter of colleges using predictive analytics are using them for registration. It is unknown what type of registration models these institutions are creating. Predictive analytics offers colleges the ability to create customized academic plans for each student. Based on a student's previous academic achievement, the student's interest, their social, personality, and economic variables and the student's career aspirations, models could be created that suggest an academic plan for all 4-years of study with success scores. These success scores can estimate the student's likelihood of degree achievement. The plan could be customized to the course level. If this type of planning was done for all students, not only could retention and graduation rates be influenced, but the institution could plan course and instructor needs for years at a time. Students could save time and money by taking courses that they will likely be successful in based on their program's curriculum. Colleges may not need as many registration and advising staff or their time could be redirected to at-risk students.

Finally, enrollment prediction modeling can allow colleges to accurately predict their enrollment, which could lead to better financial planning. This is important for all colleges but especially open enrollment institutions, such as community colleges, that are dependent on variables, like the local unemployment rate, for their students.

At-risk students**.** Almost all the respondents in this study that are using predictive analytics are using them to build at-risk student models. Nearly all of them are connecting these students to student success interventions. The examples that exist are case studies of individual institutions. For one thing, the point of intervention in the student's academic career needs to be determined. Research needs to be conducted to determine if students who are identified as at-risk prior to starting their academic program have higher student success outcomes if they are targeted with student success interventions from the start.

Institutions building at-risk student models in silos are a lost opportunity because the accuracy and predictive power of predictive models can be heightened by combining data across institutions. As noted in Chapter 2, Marist College leads the Open Academic Analytics Initiative. One takeaway from this study is that predictive models can be ported between institutions without losing predictive power. Institutions should work collaboratively with each other to share data and models. Creating thousands of variations of the same types of model (one for each college) is a waste of time and resources—there is enough of that already in higher education. Work together. Share innovative interventions. Today's student success interventions are generic. Collaborating institutions using predictive models may be able to create new interventions that lead to a better understanding of students and what helps them succeed.

Chapter 1 indicated that despite investment in student success programs, student success rates have barely changed. Sending students to academic advisors and to academic help centers were the most likely interventions that institutions use for at-risk students. These are two of the oldest strategies higher education has for student success. New strategies and interventions are needed because the current strategies have not changed student success outcomes despite millions of dollars in investment. Only 15% of institutions placed students in a specific program for at-risk students. Colleges need to measure which interventions have the most success based on a student's needs. Only then can predictive models recommend the right intervention for that student. There is information to be learned by this 15% of institutions. When do these at-risk student programs take place in the student lifecycle? Are they proactive and target the students at the beginning, or do they wait for signs of academic difficulty? Do the programs follow a protocol that could be duplicated at other institutions and studied? Ideally, students should be identified as at-risk before they ever step foot on their college's campus.

Imagine an educational environment where a student is told what college they are most likely to be successful at based on their likes, abilities, personal and financial situation. What if the students' application process was influenced by a predictive model that could tell that student what college to apply to? From there another model informs the student and the college which academic programs are the best fit for the student, as outlined above. With the student's academic journey mapped out based on the student's likelihood of success, their aptitude, and interests, the student could also be placed into academic support programs as part of their coursework. This way, at-risk students would not need to feel singled out. Perhaps they never even know they are in an at-risk program. Predictive analytics makes this a possibility by giving colleges the ability to identify at-risk students based on data known about them prior to enrollment, such as high school grades, test scores, socio economic factors, etc. The student could be flagged in college information systems and routed to certain programs based on their at-risk factors. Some may have ethical issues with this approach; however, it could be argued that labeling a student as not likely to succeed, and telling them so, would create a self-fulfilling prophecy for some students.

It is a radical shift from today's higher education to think of automating a student's academic program choices and support services at point of application, but it is one we might consider if we are serious about lowering student debt, increasing student outcomes, and spending less taxpayer dollars on students who do not succeed. If higher education was able to be revolutionized in such a way, there are challenges that come with such a model.

Addressing concerns. If the student lifecycle was impacted at all stages of academic development by predictive analytics there is the possibility students could be pigeonholed into programs they do not want or do not need. Bias in predictive models comes from missing data. Unless a model was 100% correct all the time, there would definitely be students placed in degree programs, or recommended success programs, that they do not need. Controls would need to be put in place to allow students a choice at each step of their academic journey to control for these possibilities. One control would be the student's choice. It would be important that students are given what they need to make informed decisions. In addition, if research was conducted to determine variables that negate at-risk status factors, predictive models could be updated with this data to improve accuracy of program placement.

There is also the possibility that the variables used in the predictive models could cause concern. Even though only 4% of campuses not using predictive analytics cited concern over profiling students it is definitely an issue that could arise when considering variables such as race, ethnicity, gender, etc. Students at-risk are often from vulnerable populations. Thoughtful consideration needs to take place relative to how best address these issues for at-risk predictive model creation and implementation.

Academic leaders must also address how at-risk student predictive models will be scaled. Students who are in the highest percentiles of at-risk status may be deemed unsuccessful no matter what type of intervention is attempted. This situation was witnessed first-hand at an institution the researcher worked with. The sentiment of some leaders was that scarce resources should be used for at-risk students who have a chance at success and not on those most at-risk. This is a sentiment that is frightening, particularly for open enrollment institutions like community colleges. If we deem the most at-risk students as unsuccessful from the start, how can we as leaders in good conscience accept their tuition dollars unless we are upfront with the student upon acceptance of their likelihood not to succeed? As explained in Chapter 1, students who do not complete degrees are more likely to default on student loans. If we are to believe that resources should not be used on the most at-risk students, then we must also believe that colleges have the moral obligation not to allow those students to enroll. This sentiment challenges the foundation of open access institutions, such as community colleges. It is the role of academic leaders to design a planning process that puts resources and personnel in a structure that allows any accepted students to succeed. Senior leadership must think deeply about these issues during the planning stage of the PDSA with predictive analytics model.

Role of leaders. Institutional research and effectiveness leaders must educate their institutions on the opportunity predictive analytics offer their campuses. It is not enough to build valid and reliable models. Models by themselves cannot accomplish anything. It is through intervention and effective planning, such as the model visualized in Figure 1.3, that outcomes in higher education can be changed. In Bishcel's (2011) study, he found that affordability of analytics became less of an issue when senior leadership supported the efforts. Thus, it is the responsibility of institutional research and effectiveness leaders to show senior leaders the value of predictive analytics. This can be accomplished by focusing on the connection between the predictive analytics models and strategic planning.

Institutional researchers and senior leaders must make predictive analytics part of the strategic planning process, as demonstrated in the Plan-Do-Study-Act with Predictive Analytics model, Figure 1.3. While interventions will be different depending on which college function is planning (enrollment, advancement, at-risk students, etc.), the planning process is the same. Use historical data and predictive variables to create accurate models. Use institutional researchers to do this. Also include your information technology staff. These important stewards of data ensure your data is safe, valid, and in a useable format. Next, plan interventions and make sure they have resources behind them. Make sure institutional researchers are a part of each stage of them model. They need to be there to answer questions about the model and obtain information that could make the model better. Implement strategies using empirical research standards that can answer causal questions. Intervention success and failure must be evaluated. The effects of strategies will be evaluated in the Study phase of the model. In the Act stage, use what was learned from implementation to strengthen the predictive models. Make changes to strategies based on successes and failures. Do not be afraid to fail. So much can be learned by a failed intervention, but it is important to understand why they failed. Analytics can inform which strategies were effective or ineffective. Make changes to the plan as needed. The best strategic planning efforts are not stagnant; they change based on intervention results.

Limitations

This study is limited by a response rate of 16% of the survey sample. It is possible that the survey respondents were more interested in predictive analytics than those that did not respond. This could lead to an over representation of institutions using predictive analytics.

Recommendations

Future research on predictive analytics in higher education needs to focus on the interventions and their connection to the planning process at institutions. There needs to be a systematic measurement of interventions and the impact they are having or are not having. It is not enough to test the accuracy of the predictive models institutional researchers are building. Nor is it enough to have interventions. There needs to be a connection between the two and the impact studied and acted upon, just as the Demming model with predictive analytics sets forth. It is up to the institutions implementing the Plan-Do-Study-Act Cycle with Predictive Analytics to conduct empirical research on the impact of interventions being used with predictive analytics in all areas: enrollment management, advancement, and most importantly student success.

For the 15% of colleges using predictive models to connect at-risk students to specific at-risk student program, research needs to be conducted to establish the effectiveness of these programs. The researcher in this study would have liked to measure effects the Plan-Do-Study-Act Cycle with Predictive Analytics has on student success outcomes, but that was not possible due to program timing. Thus, it is recommended that continued empirical studies are conducted by the institutions using predictive analytics. Wherever possible, institutions that can collaborate and share results is encouraged. Wherever possible, institutions are encouraged to collaborate and share results.

Finally, it is recommended that senior leaders in higher education educate themselves on the value predictive analytics offer their institutions. Survey respondents that are using predictive analytics cited senior leaders as important to the implementation of predictive analytics on their campus. Not only must they be supportive, but they need to be able to articulate the value of predictive analytics to the college community. This is not an endeavor that will be successful unless the entire leadership team is supportive. The college president must commit to this process and expect the same from his or her staff.

Conclusion

If there is one word that describes predictive analytics in higher education it is "opportunity." Predictive analytics give higher education leadership the opportunity to change how the sector has traditionally done business by providing a proactive strategic planning tool that can target interventions and resources where there is the greatest chance of success. Change in higher education is slow and often difficult, but it must happen so that millions of taxpayer and tuition dollars are not wasted on interventions that do not work. Performance based funding ties competing resources to student success outcomes. Student debt is over a trillion dollars and the debt burden for non-completers is higher. Millions of dollars in resources are being spent to help at-risk students succeed, but success rates are not changing. A change needs to take place in the business model of higher education. Predictive analytics is a tool that can catalyze this change.

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Appendix A

Survey Instrument

Predictive Analytics in Higher Education Survey

Screening Questions

1. At your institution do you have upper level responsibility or knowledge of institutional research functions? These functions may include data and analytics, predictive analytics, and the collection, analysis and reporting of quantitative data.
    a. Yes (continue to screening question 2)
    b. No (End of survey; Thank you for your participation in this survey)

2. Does your institution currently use predictive analytics (defined as statistical models of future behavior or activity made up of predictor variables that inform a future result. In higher education, examples of predictive modeling may include enrollment prediction modeling, at-risk student modeling, and, but not limited to, future donation modeling in advancement)?
    a. Yes (If yes, go to Section A question 1)
    b. No (If no, go to question Section C question 1)

Section A

1. How long has your institution been using predictive analytics?
    a. 0-2 years
    b. 3-4 years
    c. 5+ years

2. What factors contributed to the use of predictive analytics on your campus? (Select all that apply)
    a. Budgetary investment from institution
    b. Budgetary investment from grant award
    c. Staffing investment from institution
    d. Senior leadership support
    e. Technology investment by institution
    f. Interest by the institutional research/effectiveness staff
    g. External accrediting agency recommendations
    h. Pressure to influence student success outcomes
    i. Other: open ended

3. Which individuals were initially supportive of using predictive analytics on your campus? (Select all that apply)
    a. President
    b. Academic Leadership (Provost, Deans, Assistant Vice-Presidents, etc.)
    c. Chief Financial Officer
    d. Enrollment Management Leadership
    e. Advancement Leadership
    f. Institutional Research/Effectiveness personnel
    g. Information Technology personnel
    h. Full-time Faculty

4. What staff and/or faculty, if any, are currently supportive of the use of predictive analytics on your campus? (Select all that apply)
    a. President
    b. Academic Leadership (Provost, Deans, Assistant Vice-Presidents, etc.)
    c. Chief Financial Officer
    d. Enrollment Management Leadership
    e. Advancement Leadership
    f. Institutional Research/Effectiveness personnel
    g. Information Technology personnel
    h. Full-time Faculty

5. Does your institution use predictive analytics for enrollment management purposes? (Select all that apply)
    a. Yes, admissions
    b. Yes, marketing
    c. Yes, registration
    d. No
    e. No, but are planning to add predictive analytics for enrollment management in the next year

6. Does your institution use predictive analytics for advancement purposes? (select all that apply)
    a. Yes, gift giving
    b. Yes, event planning
    c. No
    d. No, but we are planning to add predictive analytics for advancement in the next year

7. Does your institution use predictive analytics to target student success outcomes, such as Retention and/or Graduation? (select all that apply)
    a. Yes, to identify at-risk face-to-face students (proceed to Section B, question 1)
    b. Yes, to identify at-risk online (remote) students (proceed to Section B, question 1)

c. Yes, to assist with student advising (If A or B is not selected, as well, end of survey with thank you message; If A or B is selected go to Section B, question1)
d. Yes, to provide course success predictions (If A or B is not selected, as well, end of survey with thank you message; If A or B is selected go to Section B, question 1)
e. No, but we are planning to add predictive analytics to target student success outcomes in the next year (go to question 8)
f. No (go to question 8)

8. If there is more information about predictive modeling at your institution you would like to share, please do so in the open ended comment box below.
(End of survey; Thank you for your participation in this survey)

Section B

1. Does your college provide a type of intervention (ex. Advising, recommendations to help center, etc.) to students that are identified as at-risk using predictive analytics?
   a. Yes (skip to Section B, question 2)
   b. No (skip to Section B, question 4)

2. What intervention(s) does your college provide to students that are identified as at-risk using predictive analytics? (Select all that apply)
   a. meeting with academic advisor
   b. referral to academic center, such as Math, Writing or Science
   c. Placement in or referral to a specific program for at-risk students
   d. meeting with instructor
   e. referral to online academic resources
   f. Other: open ended

3. If there is more information about predictive modeling at your institution you would like to share, please do so in the open ended comment box below.

(End of survey; Thank you for your participation in this survey)

4. Why doesn't your college connect intervention to the at-risk student predictive model?
   a. Lack of budgetary investment from institution
   b. Lack of staffing investment from institution
   c. Lack of senior leadership understanding of the value the connection would have
   d. Lack of technology investment by institution to connect and track the intervention
   e. Lack of planning capabilities
   f. Other: open ended

(End of survey; Thank you for your participation in this survey)

Section C

1. To the best of your knowledge has your institution considered using predictive analytics on your campus?
    a. Yes
    b. No

2. What has prevented your institution from using predictive analytics on your campus? (select all that apply)
    a. Budgetary investment from institution
    b. Budgetary investment from grant award
    c. Staffing investment from institution
    d. Senior leadership support
    e. Technology investment by institution
    f. Interest by the institutional research/effectiveness staff
    g. External accrediting agency recommendations
    h. Pressure to influence student success outcomes
    i. Other: open ended

3. Do you believe your institution will begin using predictive analytics in the next:
    a. 1-2 years?
    b. 3-4 years?
    c. 5+ years?

4. What staff and/or faculty support would be required for predictive analytics to be used on your campus? (select all that apply)
    a. President
    b. Academic Leadership (Provost, Deans, Assistant Vice-Presidents, etc)
    c. Chief Financial Officer
    d. Enrollment Management Leadership
    e. Advancement Leadership
    f. Institutional Research/Effectiveness personnel
    g. Information Technology personnel
    h. Full-time Faculty
    i. Part-time Faculty

5. What staff and/or faculty, if any, are currently supportive of the use of predictive analytics on your campus? (Select all that apply)
    a. President
    b. Academic Leadership (Provost, Deans, Assistant Vice-Presidents, etc)
    c. Chief Financial Officer
    d. Enrollment Management Leadership
    e. Advancement Leadership
    f. Institutional Research/Effectiveness personnel
    g. Information Technology personnel
    h. Full-time Faculty

i. Part-time Faculty

6. If your institution were to begin using predictive analytics, what functions do you believe it would use them for?
    a. Enrollment management
        i. Admissions
        ii. Marketing
        iii. Registration
    b. Advancement
        i. Gift giving
        ii. Event planning
    c. Retention/Graduation
        i. Identifying at-risk face-to-face students
        ii. Identifying at-risk online (remote) students
        iii. Advising
        iv. Course success
    d. Other: open response

7. If there is more information about predictive modeling at your institution you would like to share, please do so in the open ended comment box below.

End of survey; Thank you for your participation in this survey)