California Community College Administrators' Use of Predictive Modeling to Improve Student Course Completions

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California Community College Administrators’ Use of Predictive Modeling to Improve Student Course Completions

A Dissertation by

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Brandman University
Irvine, California
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Submitted in partial fulfillment of the requirements for the degree of Doctor of Education in Organizational Leadership

April 2017

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April 2017
California Community College Administrators’ Use of Data from Predictive Modeling to Improve Student Course Completions

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ACKNOWLEDGEMENTS

Throughout the coursework and now this paper, everyone has described this as a “journey.” I now understand why. It was not a straight path to an end. There were both challenges and opportunities that presented themselves in the months leading to this finished product.

I want to thank everyone who supported me in this grand endeavor. First, I want to recognize my husband, John, who fully supported my decision to pursue this doctorate and who never once criticized, complained, or balked at the time away or expense involved. He knew this was important to me, so it became important to him. Second, my daughter, Chelsea, who understood my desire to pursue additional education and who helped with the initial edits of this paper. Third, my son, Patrick, who supports me even when I am not always available and there for him. All three allowed me to immerse myself in this personal project even when it took time away from them because they knew it was valuable to me.

I want to thank those who are no longer around—my parents, Charles and Doris LeBarre. They instilled a love of lifelong learning at an early age. They provided all of their children a quality educational foundation and made many sacrifices to send all 13 of us to private schools. I remember many weekends spent at the local library—I must have read every book in that small branch. Even with this strong foundation, their primary hope for us was to be happy in our personal lives.

I want to thank Dr. Jasmine Ruys and Dr. Linda Williams for the nudge they gave me to pursue this doctorate. I have them to thank for starting the program.
I want to recognize and thank my newly added “brothers” to my family. As a cohort, our small group of five (six with our mentor, Dr. Cascamo), the Monterey Gammas Octopi, became closer than any family. We shared our trials, our challenges, our insights, and our processes, and we pushed and prodded each other to successful completions of our personal academic goals. These brothers are: Mowafiq Alanazi, Scott Dick, Sam Garzaniti, and Eric Ramones. We gave each other support and encouragement along the way. They gave me strength to persevere, helped keep me on track, and were my cheerleaders to keep going and pushing through when I thought I would not finish according to my timeline.

Many thanks to those participating in the study. It could not happen without you. I want to thank my cohort leader and committee member, Dr. John Cascamo. Without his suggestion of using my transformational change project as a possible dissertation topic, I might have chosen a topic that did not resonate with and inspire me as this one did. I also want to thank Dr. Len Hightower for his initial work helping me to focus on the key points of my topic while creating my prospectus and then taking on an additional role as a member of my committee. Lastly, I want to acknowledge Dr. Tod Burnett for his work chairing my committee while maintaining a busy family life and schedule, presiding as a community college president, mentoring his own Brandman cohort of doctoral students, and chairing other Brandman doctoral students’ research.

This research does not end the journey. It is the beginning of a new journey with eyes wide open and new paths to explore.
ABSTRACT

California Community College Administrators’ Use of Data from Predictive Modeling Software to Improve Student Course Completions

by Rita D. Grogan

Purpose: The purpose of this case study was to determine the impact of utilizing predictive modeling to improve successful course completion rates for at-risk students at California community colleges. A secondary purpose of the study was to identify factors of predictive modeling that have the most importance for improving successful course completion rates for at-risk students as perceived by California community college administrators.

Methodology: This case study identified specific administrators at five community colleges within two California community college districts using predictive modeling to improve successful course completion rates. Participants were chosen based on specific criteria. The study was designed to collect data through interviews, documents and archival sources to answer the research questions.

Findings: These findings were identified as impacts: (1) no discernable improvement in course completion rates; (2) student contact, (3) timely intervention strategies; (4) identify and monitor students; (5) sufficient support services; (6) successful completions and retentions to achieve educational goal; and (7) institutional metrics and reporting.

The findings identified as important factors were: (1) planning and strategy; (2) communication and training; (3) resources; (4) outcomes; and (5) inclusion.

Conclusions: It is too early to determine any impact on successful course completion rates by using predictive modeling software. A diverse population of stakeholders must
jointly determine the outcomes desired from and identify the data needed to accurately analyze and model predictions. These data streams allow policy decisions to start with data. Predictive modeling software is a tool to identify students for timely and specific interventions. Increasing a student’s sense of belonging, engagement, and awareness is important to successful course completions. Administrators need assistance with and exposure to data analytics and predictive modeling to establish a data-driven decision-making culture. A culture of continuous review and improvement of the predictive models should be established.

**Recommendations:** Provide administrators and other personnel with professional-development learning activities related to using data to inform policy and procedures that encourage student engagement, strategies for student success, and a cycle of continuous review and improvement.
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CHAPTER I: INTRODUCTION

In 1990, the United States (U.S.) ranked first among 20 countries (Table 1) studied by the Organization for Economic Cooperation and Development (OECD) in the world for four-year college-degree completions according to De La Fuente and Domenech (2001) and others (National Center for Education Statistics [NCES], 2013; U.S. Department of Education [USED], 2011; Werner, 2010). While there has been an increase in U.S. college completions since 2009, the U.S. ranking (Table 2) has slipped to 19th place worldwide ("OECD," 2014, Chart A3.3). When international students are removed from the counts (Table 2), the U.S. ranking improves slightly to 15th ("OECD," 2014, Chart A3.3).

President Barack Obama in a 2009 speech to Congress indicated that the U.S. could not successfully compete in the world marketplace without a more educated workforce, and further stated that higher-education reforms were needed to produce college graduates sufficient in quantity and quality to address the changing needs of the global economy (The White House Office of the Press Secretary [White House Press Secretary], 2009). A U.S. agenda was established to increase the rate of college attainment and completion by 2020 to again rank the U.S. as number one for higher education completions internationally (The White House [White House], 2011; USED, 2011). President Obama identified U.S. community colleges as playing a significant role in increasing the number of students pursuing and completing transfer coursework, certificates and associate degrees (White House Press Secretary, 2009; White House, 2011). However, a large number of community college students are not completing their
educational goals, thus complicating the attainment of this U.S. 2020 completion goal (Werner, 2010).

Student persistence leading to completion was identified as a factor in reaching the U.S. goal (White House, 2011; USED, 2011). Only 47% of students who start a college program in the U.S. obtain a degree or certificate (Tinto, 1993; American College Testing [ACT], 2015; Schwartz, 2010). According to data provided by the National Student Clearinghouse and analyzed by Fain, “more than thirty-seven percent of college students transfer at least once within six years” (Fain, 2015, para. 1) when looking at 2008 first-time college students.

Table 1.

1990 OECD post-secondary degree completion (graduation) rankings by country

<table>
<thead>
<tr>
<th></th>
<th>Country</th>
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<tbody>
<tr>
<td>1</td>
<td>United States</td>
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<tr>
<td>2</td>
<td>Australia</td>
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<tr>
<td>3</td>
<td>New Zealand</td>
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<td>4</td>
<td>France</td>
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<td>Germany</td>
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<td>15</td>
<td>United Kingdom</td>
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<td>Austria</td>
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<td>17</td>
<td>Greece</td>
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<td>18</td>
<td>Spain</td>
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<td>19</td>
<td>Portugal</td>
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<td>20</td>
<td>Italy</td>
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</table>

Note: (De La Fuente & Domenech, 2001, Table 4)
Astin (1999), Kimbark (2015), and Pascarella and Terenzini (2005) suggest both student engagement and involvement while attending college play significant roles in persistence. Other researchers (Webber, Krylow, & Zhang, 2013) agreed that the more involved and engaged students become in the academic and social aspects of college life, the more likely the students would persist and complete their education.

Table 2.

**Worldwide 2012 graduation rankings by country as percent of population**

<table>
<thead>
<tr>
<th>Rank including International Students</th>
<th>Country</th>
<th>Rank excluding International Students</th>
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<tr>
<td>1</td>
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<td>New Zealand</td>
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<td>3</td>
<td>Poland</td>
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<tr>
<td>4</td>
<td>Australia</td>
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<td>5</td>
<td>Denmark</td>
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<td>6</td>
<td>Finland</td>
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<td>Ireland</td>
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<td>8</td>
<td>Netherlands</td>
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<td>9</td>
<td>Japan</td>
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<tr>
<td>10</td>
<td>Slovak Republic</td>
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<td>11</td>
<td>Slovenia</td>
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<td>12</td>
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<td>Portugal</td>
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<td>Israel</td>
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<td>16</td>
<td>Czech Republic</td>
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<td>Sweden</td>
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</tr>
<tr>
<td>19</td>
<td><strong>United States</strong></td>
<td><strong>15</strong></td>
</tr>
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</table>

*Note. 2012 data as reported by OECD in 2014*

To incentivize colleges’ creation of practices leading to student persistence and completion, a growing number of states are moving toward performance-based funding models that measure student completions (Layzell, 2007; National Conference of State Legislatures [NCSL], 2015). Because of this, community colleges are being held accountable for specific outcomes and performance standards and are experiencing
increased fiscal and national completion pressures to identify ways to help students persist toward the completion of their college degrees (Layzell, 2007; NCSL, 2015; Polatajko, 2011).

This can be especially problematic for community college students, many of whom enter college unprepared for college-level coursework and are more at risk of dropping out and not completing their certificates or degrees (Bulger & Watson, 2006; Nettles & Millett, 2000; Pascarella & Terenzini, 2005). Statewide, California’s community college chancellor’s office reported that only 39.6% of students who entered in academic year 2009-10 attained a degree, certificate, or transferred by the end of academic year 2014-15 (California Community College Chancellor’s Office website, 2016). Additionally, of the total number of unprepared students who entered California’s community colleges in 2009-10, only 65.8% completed at least 30 units by the end of their sixth academic year, 2014-15 (California Community College Chancellor’s Office website, 2016).

Community colleges may not be able to influence student academic and life experiences prior to entry but can provide experiences and encourage engagement while the student is enrolled (Astin, 1999; Polatajko, 2011; Porchea, Allen, Robbins, & Phelps, 2010; Schwartz, 2010). Community college administrators are moving to a variety of data-driven resources and tools to identify those students who may be at risk of not persisting (Bachler, 2013; Bailey & Alfonso, 2005; Beaudoin & Kumar, 2012; Dorsey, 2014; Reyes, 2015) and making changes to policies and practices that can help these students persist to completion. In particular, administrators are turning to a process called predictive modeling, where multiple sources and types of data are combined and
analyzed to predict or forecast future student behaviors and outcomes. By using predictive modeling software, administrators identify and concentrate practices and services toward those students who are showing warning signs of not successfully completing their courses (Delen, 2011-12; Kuk & Banning, 2009; Whalen, Saunders, & Shelley, 2009-2010).

**Background**

Four primary areas were considered in this research. First, persistence in course completions toward higher-education degrees and certificates were reviewed as a measure of student success. Second, student course completions in combination with student engagement and institutional accountability using performance-based outcomes for funding of services were studied. Third, an examination of potential impacts, caused by legislation and related funding models, on the expected roles of the community college to increase student course completions occurred. Fourth, the utilization of data, including predictive modeling, by community college administrators to make changes to improve student persistence was reviewed.

**Success of U.S. Students in Higher Education**

A more educated workforce is needed in the U.S. to effectively compete in the changing and growing global economy (The White House Office of the Press Secretary [White House Press Secretary], 2009). Economic activity significantly decreased in the U.S. from late 2007 through mid-2009. This time period in the U.S. was named the Great Recession (Bureau of Labor Statistics [BLS], 2012; Rampell, 2010; Shierholz, 2014). While all occupations were affected by this downturn in the economy, those workers who had attained some level of higher education were more likely to find employment than
other workers (BLS, 2012; Rampell, 2010; Shierholz, 2014). In 2009, U.S. President Barack Obama indicated in a speech to Congress that, unless changes were made to its educational system, the U.S. would not produce enough college graduates to allow the country to effectively compete in the world marketplace (White House Press Secretary, 2009). President Obama also stated that higher-education reforms were needed to produce college graduates sufficient in quantity and quality to address the changing needs of our global economy (The White House Office of the Press Secretary [White House Press Secretary], 2009). The U.S. identified and established an agenda in 2009 to increase the rate of college attainment and completion by 2020 that would allow the U.S. to again rank number one internationally for higher education completions when compared to total population (The White House [White House], 2011; USED, 2011). This 2020 completion rate requires a 50% increase from 2009 numbers (USED, 2011).

According to the National Center for Education Statistics, the proportion of 25-to-29-year-olds of the U.S. population completing at least a bachelor’s degree in 2014 was 34% (National Center for Educational Statistics [NCES], 2015). The national completion agenda seeks to increase the rate of college attainment and completion of associate degrees and certificates or higher by an average of 50% from 2009 levels, thus allowing the U.S. to regain its number-one spot in the world (U.S. Department of Education [USED], 2011; Werner, 2010). Each state has a role to play to meet the 50% national achievement goal as set by President Obama in 2009 (USED, 2011; White House Press Secretary, 2009). California seeks to increase the college attainment and completion rate by almost 60% from the state’s 2009 levels to assist the nation to reach the 2020 goal of college attainment and completion (USED, 2011). The total number of students in
California who start college is sufficient to meet the state’s 2020 goal if they stay in school and complete their courses (USED, 2011). However, large numbers of students are dropping out and not completing their education goals (Werner, 2010). Persistence leading to completion is a factor in reaching the 2020 national goal (The White House [White House], 2011; USED, 2011).

**Student Persistence in Higher Education**

Forty-seven percent of those students pursuing a higher-education certificate or degree in the U.S. fail to complete (ACT, 2015; Schwartz, 2010; Tinto, 1993). For public two-year colleges, the completion trend, referenced as graduating within three years from 1983-2015, decreased from its highest level of 38.8% in 1989 to its current level of 21.9% in 2015 (American College Testing [ACT], 2015). Torraco and Hamilton (2013) believe there is a growing educational gap created by a lack of students pursuing and completing higher education degrees that will provide them with the competencies and skills required of the future U.S. workforce. Torraco and Hamilton (2013) and others (White House Press Secretary, 2009; Werner, 2010) believe that this lack of higher education attainment, if not addressed, may result in social and economic downturns in the United States.

**Student engagement and involvement.** Tinto (1975, 1993) provided a model of the social and economic impacts of students dropping out of college. Other researchers (Astin, 1999; Kimbark, 2015; Pascarella & Terenzini, 2005) elaborate on Tinto’s initial theory and suggest both student engagement and involvement while attending college plays a significant role in retention. Engagement was identified from the simple to more complex—making friends, social activities on campus to formal study groups and
structured tutoring sessions (Webber, Krylow, & Zhang, 2013). Webber et al. (2013) agreed that the more involved the student was in the college community, the more likely that the student would persist and succeed both academically and socially. According to Kelley-Hall (2010), student support services create social and academic experiences that provide students with opportunities to become involved in campus activities. Students engaged in campus life interact with other students, faculty and staff. These student interactions generated a sense of belonging and well-being “by creating an environment connected to involvement and achievement” (Kelley-Hall, 2010, p. 148). However, many community colleges may not have the needed funding and staff resources to effectively scale up these student support services that acclimate a student to college life.

**Institutional accountability.** Legislatures in many states are beginning to look at changing the way they fund higher education as taxpayers resist funding models where positive outcomes are not achieved (Polatajko, 2011). Layzell (2007) indicates that there were five common funding approaches used by states. The predominant model, used by 38 of 50 states, is a simple reimbursement formula based on expenses to educate full-time equivalent students (FTES) (Layzell, 2007). However, by mid-July 2015, the National Conferences of State Legislatures reported that 32 states had moved away from funding formulae based on simple counts of students to ones that are based on performance or specific outcomes like completions or graduations. Another five states were looking at moving to performance-based funding (National Conference of State Legislatures [NCSL], 2015). As some states consider a move to performance-based funding models, both Layzell (2007) and Polatajko (2011) note that funding commitments may change depending on external influences like public perceptions of value, economic upheaval, or
changing educational practices or trends. Additionally, Layzell (2007) and Polatajko (2011) report that some community college administrators do not believe their funding should depend solely on performance or outcomes. Because of open admission and access policies at their colleges, some administrators believe that they have less influence over students’ retention leading to completion and, therefore, their funding sources and allocations should not be affected by these rates (Layzell, 2007; Polatajko, 2011).

American College Test (ACT) data show the current community-college completion trend for those students graduating in three years or less at less than 30% nationwide (ACT, 2015). After the first year of college attendance, the average annual dropout rate at two-year colleges of traditional-age students, ages 18-24 years, remains the highest at 27% and is more than double that experienced at four-year colleges (American College Testing [ACT], 2015). While these trends have remained fairly constant over the six years shown in ACT’s 2015 analysis, U.S. President Obama’s college-completion agenda strives to increase the numbers of college student graduations (White House Press Secretary, 2009).

**Legislation and funding.** Federal and state legislative bodies demand that government funds given to institutions of higher education be spent wisely toward retaining and graduating students (Layzell, 2007; NCSL, 2015; Polatajko, 2011). Increasingly, recent legislation requires community college funding to have a basis in specific outcomes and performance standards (NCSL, 2015). Most of these standards involve student persistence (staying in college) and degree completion (Layzell, 2007; NCSL, 2015). Student success, defined as staying in college, completing courses, attaining an associate degree or certificate, or transfer, has become an accountability item
for colleges. According to the American Association of Community Colleges ("CC Future," 2000), students have more higher-education options and choices available to them requiring community colleges to adjust their instructional and support services to meet students’ and potential employers’ evolving requirements.

**Role of the community college.** Since 1901, with the founding of Joliet Junior College in Illinois, U.S. community colleges have offered higher education opportunity and choice to the American public ("CC History," 2000). The community college fills a niche that responds to community requirements and workforce needs (California Community Colleges Chancellor’s Office [CCCO], 2013). With more than half of the nation’s undergraduate population educated by community colleges, they retain their identities as individual colleges but share common visions of access and providing services ("CC History," 2000; NCES, 2013). Only 20% of community college students transfer to a four-year college or university but, of those, 60% earn a bachelor’s degree in four years and another 12% persist after four years to achieve their degree objective (Fain, 2012). These percentages increase to 71% graduation rates within four years and 80% after four years when a student completes an associate degree (Fain, 2012).

Currently, the community-college mission includes open-access admission policies ("CC History," 2000; Layzell, 2007; Polatajko, 2011). California community colleges continue to admit and enroll students throughout the academic year (CCCO, 2013). Additionally, California community colleges’ missions provide opportunities for full- and part-time students, those seeking transfer for four-year degrees, and those hoping to expand their career knowledge and job skills (CCCO, 2013; Shannon & Smith, 2006). There is a current push by taxpayers and related funding mechanisms to
have community colleges focus their education efforts on higher degree-seeking students (Layzell, 2007; Nettles & Millett, 2000). However, many of these students are underprepared to successfully complete college-level coursework (Bulger & Watson, 2006), much less seek transfer admission at four-year institutions.

**Students at Risk of Not Persisting**

The prime community college mission is to provide access to all students who meet the basic entrance eligibility requirements (CCCCO, 2013). Many of these students are considered more part of the “New Majority students—displaced workers, single parents, immigrants, first generation or older” than those referred to as traditional college-age students, aged 18 to 24 years old (Bulger & Watson, 2006, p.23). This population looks to the community college system to support them toward the successful completion of their education goals (Astin, 1999; Schwartz, 2010). Many in this group are underprepared for college-level coursework and college society, and include those identified as at risk of not persisting to completion (Nettles & Millett, 2000; NCES, 2015; Pascarella & Terenzini, 2005). A publication of the Education Advisory Board (EAB) identified students at risk of not persisting as those who “encounter academic challenges; do not engage socially in the campus community; or encounter financial challenges” (Beaudoin & Kumar, 2012, p. 8).

The support services provided to these populations are as diverse as the groups making up the population (Kimbark, 2015; Schwartz, 2010; Smith, 2013). Some of the support strategies that are addressed or recognized in the literature are counseling and academic advising (Zhang, Fei, Quddis, & Davis, 2014), tutoring in reading, writing, and math, and helping them advance in technological skills and capabilities needed in twenty-
first century higher education institutions and workplaces (Bulger & Watson, 2006). However, other researchers such as Webber et al. (2013) believe student engagement and involvement in both curricular and co-curricular activities are necessary to contribute to student success. Types of activities under the general heading of student engagement may include making new friends, joining study groups, and membership in student clubs. These activities help students become acclimated to the college and create a sense of belonging. Webber et al. (2013) also concluded that students who actively prepared (studying, assignment completions) for class received higher grades and were more satisfied with their college experience.

**Efforts to Support Student Persistence**

In 2012, community colleges enrolled 46% of all students in public higher education institutions (NCES, 2013). Enrollment patterns at community colleges, because of their open admissions policy, reflect students attending part- and full-time and those who are typically underserved or need assistance to complete their educational goals (American College Testing [ACT], 2010; Schwartz, 2010). Because federal and state funding of community colleges has become closely associated with performance-based outcomes, community colleges link success with students staying in school and completing their educational goals (Layzell, 2007; NCSL, 2015). Because of this, community colleges use a broad-based set of engagement and involvement strategies and practices to meet the unique academic and social needs of their student population (Bailey & Alfonso, 2005; Schwartz, 2010; Zhang et al., 2014).

Astin, (1999), Polatajko (2011), Porchea et al. (2010), and Schwartz (2010) postulate that community colleges cannot directly influence student life experiences prior
to entry. However, Schwartz (2010) further states that community colleges can present academic experiences to and encourage engagement with the student while in attendance. Schwartz (2010) continues to reflect that positive experiences in the form of institutional behaviors and practices may influence the students’ willingness to stay in college and complete their academic goals. Community colleges often discover that a student has dropped out after the event occurred and, many times, without an intervention strategy convened (Beaudoin & Kumar, 2012).

**Course Completions**

Many researchers (Astin, 1997; Astin & Oseguera, 2005; Bean & Eaton, 2001; Bergman, Gross, Berry, & Shuck, 2014; Nodine, Venezia, & Bracco, 2011; Tinto, 1993, 2004; Whalen, Saunders, & Shelley, 2009-2010) link successful student completion to certificate and degree attainment or eligibility for transfer. While obtaining credentials or transferring are outcomes that students desire to achieve, student completions at the course level are needed to reach those goals. However, some researchers (Adelman, 2005; Astin & Oseguera, 2005; Bachler, 2013; Bailey, et al., 2005; Beaudoin & Kumar, 2012; Dorsey, 2014; Vance, 2009) believe that course completion rates may be predicted when student characteristics, behaviors and support services are analyzed.

Whaley (2015) found several relationships that positively impacted students’ remedial course completions. Whaley (2015) stated that a student’s age may play a role in increasing remedial course completions—the older the student, the more likely the course would be completed. Receipt of financial aid, depending on the types and amounts received, was also found to increase remedial course completions (Whaley, 2015). A third finding of Whaley (2015) indicated that the type of remedial course—for
example, math or English—was an indicator of increased course completions. Whaley (2015) found those students in his sample attempting English were more likely to complete their courses than those taking math. While there are many potential student characteristics that may influence course completions (Whaley, 2015), there is a vast array of data that captures student characteristics prior to starting college coursework, student behaviors when enrolled in a course, and outcomes from both successful and unsuccessful course completions (Astin, 1999; Bailey et al., 2005; Borghese & Lacey, 2014; Tinto, 1988, Yaghmaee, 2013).

**Knowledge Mobilization**

Knowledge mobilization (KMb) has been described as a convergence between research and evidence toward changing policy and practice (Levin, 2013). By using the term *mobilization*, “it indicates that this work requires specific effort, over time, working with others, and involves much more than telling people about research findings” (Levin, 2013, p. 2). Levin (2013) suggests that KMb is an interactive multi-directional process involving people reviewing data-derived information and relating it to institutional practices (Figure 1).

Historic data are available to review when a student drops out of college. Additionally, data are available that may identify certain behavioral and academic predictors common among student populations at risk of not persisting. These historic data, when combined and analyzed with current data reflecting student behavior and activity, models and identifies the possibility of an event before it happens (Essa & Ayad, 2012; Macfadyen & Dawson, 2009; Porchea, Allen, Robbins, & Phelps, 2010). This type of data modeling can predict college student behaviors as a collection of items that lead
to a particular outcome (dropping out) (Bailey & Alfonso, 2005; Beaudoin & Kumar, 2012). Predictive modeling can identify positive outcomes, such as staying in college, as well as determinations that would indicate at-risk behaviors (Dorsey, 2014).

**Figure 1.** Moving data to inform decisions. Conceptualizes functions and their relationship flow (Levin, 2013, Figure 1).

The results of this modeling may then be used to provide interventions to prevent dropping out (Bailey & Alfonso, 2005; Beaudoin & Kumar, 2012; Dorsey, 2014).

**Data-Driven Decision-Making**

Institutions may have many collection points for and resources of data (Bachler, 2013; Dorsey, 2014; Macfadyen & Dawson, 2009). Predictive modeling takes the collected data from these sources and analyzes it to predict possible student behaviors (Beaudoin & Kumar, 2012; Dorsey, 2014; Reyes, 2015).

Multiple state and federal initiatives suggest a move to data-driven decision-making to identify intervention strategies to prevent student attrition (Beaudoin & Kumar, 2012; NCSL, 2015). Marsh, Pane, & Hamilton (2006) suggest two primary types of decisions that come from “actionable knowledge”—“those using data to inform,
identify, or clarify (e.g., identifying goals or needs) and those that entail using data to act (e.g., changing curriculum, reallocating resources” (p. 3). A conceptual model, adapted in Figure 2, was created by Marsh et al. (2006) to show that there are many types of data used and available along with a typical movement of this information toward data-driven decision-making.

**Figure 2.** Conceptual framework of data-driven decision-making in education

**Predictive Modeling**

While many community colleges lack comprehensive institutional research departments and staff, data are available for collection and analysis (Polatajko, 2011). Although predictive modeling is a useful decision-making tool to identify those students
potentially at risk, the data analysis must be accessible, reliable, usable, and understandable to benefit community college administrators (Dorsey, 2014; Marsh et al., 2006)). Using these predictive models to make data-driven decisions, administrators may then create, enhance or revise policies and practices related to intervention strategies that keep students in school (Bachler, 2013; Delen, 2011-12; Keys, 2013; Whalen, Saunders, & Shelley, 2009-2010). In particular, community college administrators are turning to data-identified models to make decisions to identify and concentrate efforts to students at risk of non-completion (Delen, 2011-12; Whalen et al., 2009-2010). The administrators’ evolving role is to ensure that the policies, procedures, programs, and services offered to students at risk of non-completion are viable, timely, and appropriate (Kuk & Banning, 2009; Dorsey, 2014).

**Administrator Roles**

Administrators oversee the most complex parts of the community college organization (Dorsey, 2014; Kuk & Banning, 2009). The departments, divisions, and areas responsive to external and internal pressures created from expectations of student success typically are under administrator jurisdiction and range from student government, classified staff, to counseling and instructional faculty (Kuk & Banning, 2009). Kuk and Banning (2009) state that the administrators tend to have more direct reports who oversee part of the practices and services that help at-risk students. While organizational structures differ from one college to the next, the role of the administrator is to assist the institution toward its mission and goals of student success (Kuk & Banning, 2009).

Data collection, analysis and review play an important role in data-driven decision-making by administrators interested in student retention at California
Community colleges (Callery, 2012). Dorsey (2014) suggests that most community college administrators currently use data only to review enrollments and budgets. However, there is no clear understanding of how, or if, administrators use predictive modeling to identify and make institutional changes that may lead to improved student course completion (Dorsey, 2014; Callery, 2012; Ewen, 2015). Additionally, there may be barriers or deterrents like limited funding and staff resources that administrators face when trying to implement data-driven decisions that change intervention strategies (Dorsey, 2014; Kuk & Banning, 2009). Callery (2012), Dorsey (2014), and Ewen (2015) suggest that further research is needed to build “a culture of evidence to support student success” (Dorsey, 2014). By pursuing this research, a better understanding of data-driven decisions, specifically data analytics and predictive modeling, as used by administrators to increase student persistence at California community colleges was explored.

**Statement of the Research Problem**

Community colleges perform an important function in the attainment of increased retention and course completion rates by creating pathways that allow students to access, transfer and complete college certificates and degrees (Nettles & Millett, 2000; White House Press Secretary, 2009; White House, 2011). The community colleges provide services that assist students’ persistence and completion efforts toward their degree objectives (Beaudoin & Kumar, 2012; Kimbark, 2015; Schwartz, 2010). These services include but are not limited to tutoring, counseling, advising, educational planning, and financial aid. Overseeing those services at California community colleges are several administrators (CCCCO, 2014; Kuk & Banning, 2009; Smith, 2013).
Many of the California community college administrator roles are to create, coordinate and oversee comprehensive, broad-based services in support of student retention and course completions (Akoma, 2012; Smith, 2013). These services provide opportunities for students to engage in the community-college experience through academic and social interactions with other students, faculty, and staff (Akoma, 2012; Callery, 2012; Dorsey, 2014; Webber et al., 2013). As a result of that involvement, Webber et al. (2013) believe that students will stay in school and complete their academic objectives. However, administrators must balance those practices leading to student retention and success with individual student academic and social needs (Akoma, 2012). Comprehensive data analyses identifying at-risk student behaviors help an administrator direct best practices and services to these students to keep them in school (Beaudoin & Kumar, 2012; Callery, 2012; Delen, 2011-12; Dorsey, 2014).

As community college administrators look more closely at data to improve processes that support students staying in school, Callery (2012) suggests encouraging a general culture of inquiry and evidence throughout the institution that assesses and re-assesses program information for viability, performance, and usefulness. Dorsey (2014) adds that community colleges already collect and store assorted and diverse data on their students, but little is done with that data as a means to make institutional improvements to increase strategic outcomes like retention and completion rates of its students. In a 2005 report from the Lumina Foundation, “accountability policies require institutions to report data that are never actually used” (Dowd, 2005, p.1) and suggest college administrators continually question, analyze, and engage in professional dialogue about their data to achieve change and improvements in student course completions. By encouraging
administrators moving to data-driven decision-making using predictive modeling tools, students may be provided individualized intervention strategies unique to their personal needs and experiences (Bachler, 2013; Beaudoin & Kumar, 2012; Callery, 2012; Essa & Ayad, 2012).

However, it is unclear how administrators use the data available to them to make changes to those policies, procedures, programs or services that affect student persistence and completion (Callery, 2012; Dorsey, 2014; Smith 2013). The exact nature of those changes is unknown (Callery, 2012; Dorsey, 2014). Callery (2012) suggests research is needed to identify “data infrastructure design considerations” (p. 241) that may help create more comprehensive data-mining and analytic reports to support improved practices toward student retention and completion. Grodzicki (2014) suggests further research is needed to provide a “more comprehensive analysis of the use of systematic evidence in reforming educational practices” (Grodzicki, 2014, p. 141). Additionally, new training and skill-building may be transferred to other administrators by identifying these changes and how data drove the decision-making process.

**Purpose Statement**

The purpose of this case study was to determine the impact of utilizing predictive modeling to improve successful course completion rates for at-risk students at California community colleges. A secondary purpose of the study was to identify factors of predictive modeling that are most important for improving successful course completion rates for at-risk students as perceived by California community college administrators.
Research Questions

RQ1: What was the impact of utilizing predictive modeling to improve course completion rates for at-risk students at California community colleges?

RQ2: What factors of predictive modeling have the most importance for improving successful course completion rates for at-risk students as perceived by California community college administrators?

Significance of the Problem

Torraco and Hamilton (2013) predict that if the U.S. does not build up the number of residents with higher education degrees, the U.S. will experience an economic and social decline that will not allow it to compete in the global marketplace. According to Carnevale, Smith, and Strohl (2010), the state of California alone will have 68% of its jobs requiring a minimum level of higher education by the year 2018. Without having a sufficient pool of potential employees with a postsecondary education, the U.S. middle class will continue to decline and widen the gap between those who have and those who have not (Carnevale, et al., 2010; Torraco & Hamilton, 2013). If the economic gap continues to widen, there may be an increase in the poverty rate, a decrease in the standard of living, an increase in the offshoring of jobs to those employees in other nations who have attained a higher education, and the potential for those have-nots without jobs or education to feel marginalized and without a voice (Torraco & Hamilton, 2013). As the demand for increasing levels of education increases, so does the expectation that college and universities increase the number of students graduating and completing programs by using all available tools (Akoma, 2012; Carnevale et al., 2010; Delen, 2011-12).
In 2009, California’s 25-to-34-year-old population of young adults represented 12.6% of the U.S. population in degree attainment (USED, 2011). By 2020, the U.S. goal asks California to increase its level of graduation attainment to 14.4% or another 1.8 million young adults with degrees and certificates (USED, 2011). Using 2007 data as a baseline, when 21.3% of the U.S. full-time equivalent students enrolled in California’s community colleges, California’s public community colleges would be responsible for more than 1 million additional completions (Community College League of California [CCLC], 2010). Toward this achievement, some California community college administrators have implemented predictive modeling software to forecast and identify those transfer-seeking students at risk of not persisting toward their educational goals (Bachler, 2013; Callery, 2012; Delen, 2011-12; Dorsey, 2014). Callery (2012) states “community college leaders must assume the role of change agents to manage the transformation of their organizations to fully integrate strategic planning initiatives, such as data-driven decision-making to enhance institutional effectiveness” (p. 216). Callery (2012) further suggests that additional study is needed to determine if there are shared data-analytic approaches used by community college administrators “to manage college operations, services and academic programs” (p. 241). Ewen’s (2015) research noted that there was a “general lack of clarity related to the use of data with the greatest potential to impact the student learning, success, and degree completion.” (p. 96). For administrators at these California community colleges who use predictive modeling data, it is unclear how they make use of the data available to them to make changes to those policies, procedures, programs or services that affect student retention and completion (Alt, 2012;
Callery, 2012; Dorsey, 2014; Ewen, 2015; Smith, 2013). Additionally, the exact nature of those changes is unknown.

As internal and external pressures mount on community colleges to provide evidence-based solutions to increase student persistence and completion (Polatajko, 2011; Torraco & Hamilton, 2013), community college leaders must determine if they “are using the data for a meaningful restructuring of the delivery of programs and services” (Sanchez, 2010). This study will increase the body of knowledge related to community college administrators and their data-driven decision-making to increase student persistence toward completion. As a result of this study, new training and skill-building may be determined and transferred to other administrators by identifying these changes and how data and actionable knowledge drove the decision-making process.

**Definitions**

For consistency of use and ease of understanding, the following terms are defined.

**Actionable knowledge.** Usage of data that allows informed decision-making to affect policy, practices, services, and programs.

**At-risk student.** A student who is in jeopardy of not successfully completing a course or courses.

**Course completion.** The act of receiving a final grade in an academic course.

**Chief Student Services Officer (CSSO).** Those upper-level administrators at California community colleges who oversee student support services.

**Data analytics.** The examination and exploration of data from any source or sources to make decisions or draw conclusions.
Data-driven decision-making. As defined by Provost and Fawcett (2013), “the practice of basing decisions on the analysis of data rather than purely on intuition” (p. 53).

Educational goals. The pursuit of student-identified academic objectives at a California community college district.

Enrollment count. The number of course enrollments with grade or notation of record of A, B, C, D, F, P, NP, I, IPP, INP, FW, W, or DR.

Higher education. All private, public, and propriety post-secondary institutions, both two-year and four-year, that provide transfer opportunities and/or terminal certificates and degrees.

Knowledge mobilization (KMb). The combination of multiple sources of data that allow users to “inform policies and practice, enhance or improve services, and/or informs decisions and/or processes” (Social Sciences and Humanities Research Council website, 2015, Definition Knowledge Mobilization) to positively influence outcomes and objectives.

Persistence. Refers to the act of completing an academic course with an equivalent to a grade of C or higher. In some instances, persistence may also indicate term-to-term enrollment completion.

Predictive modeling. Predictive modeling software is an automated, programmed process where multiple sources and types of data are analyzed to forecast future behaviors and outcomes.

Retention count. The number of course enrollments with grade or notation of record of A, B, C, D, F, P, NP, I, IPP, INP, or FW.
**Student support services.** Student support services are those services supplemental to traditional in-class instruction that may include tutoring, counseling, advising, financial support, and other like services. These services include any assistance offered by the college to the student as encouragement to course completion.

**Success count.** The number of course enrollments with grade or notation of record of A, B, C, P, IA, IB, IC, or IPP.

**Successful course completion.** The act of receiving a grade of C, or its equivalent, or higher in an academic course.

**Transfer-seeking student.** Intention to complete sufficient coursework that would allow admission to another college or university for attainment of a higher educational degree.

**Delimitations**

This study was delimited to chief student service officers (CSSO) employed at California community colleges that purchased predictive modeling software and who received training or exposure to its utilization.

**Organization of the Study**

There are five chapters, a reference list, and appendices contained in this dissertation. Chapter I includes the introduction, background, and purpose of the study, identifies the research questions, provides the significance of the study, its delimitations and definitions of terms. Chapter II reviews the literature associated with the purpose of the study, especially as it relates to student attrition and course completions, collection of data, and predictive modeling software data used by community college administrators to increase student course completion rates. Chapter III presents the research design and
methodology as it relates to the case study, describes how the population and sample were selected, and details the data-collection process, including the use of interviews and archival data. Chapter IV reviews the data collection and analyses. Chapter V presents a summary of the study, the findings and conclusions, and suggested future research.
CHAPTER II: REVIEW OF THE LITERATURE

In this chapter, a review of relevant literature and research first focused on the U.S. higher-education completion agenda leading to the specific roles community colleges play to increase student course completions toward degrees and certificates. This chapter begins by researching the national higher-education completion agenda as it relates to community colleges in general and those in California in particular, and looks at a changing landscape that includes increased funding and resource accountability based on student performance toward their educational goals. The research included a review of seminal studies of student persistence and completion; the importance of student engagement and involvement in completion; and the responsibilities assumed by California community colleges to increase course completions. Continued review of the literature included student course completions as an indicator of institutional effectiveness. Additional study of the literature considered reasons students persist and how to predict and identify those students who are at risk of not persisting. Community colleges’ efforts to support student course completion by using multiple and disparate data sources to inform change-making decisions were studied. A key concept of knowledge mobilization, moving from data to practice, was examined. Predictive modeling, as a tool used in data-driven decision-making, was reviewed and included. Finally, the use of data by administrators to inform decisions that impact practices to increase successful course completions by students was reviewed.

Higher-Education Completion Agendas

The United States (U.S.) is now ranked 19th out of 28 nations in higher-education graduation rankings by percent of population within country, when including
international students, and 15th when excluding international students in the data compilations (OECD, 2014), falling far from the number-one spot it held in 1990 (USED, 2011). This ranking places us behind Iceland, New Zealand, Poland, Australia, Denmark, Finland, Ireland, the Netherlands, Japan, Slovak Republic, Slovenia, Norway, Portugal, Latvia, Israel, Czech Republic, Australia, and Sweden (OECD, 2014). President Barack Obama recognized a need to re-establish the U.S. as the number-one country that encourages and emphasizes an educated citizenry to compete in a global economy (White House Press Secretary, 2009; The White House website, 2011; USED, 2011). President Obama further stated that higher education institutions, especially community colleges, play a significant role in the U.S. completion agenda of reaching its 2020 goal of regaining the number-one ranking globally in graduation completions relative to total population (NCES, 2013; USED, 2011; Werner, 2010). In support of this, community colleges continue to serve as common entry points to higher education for more than 45% of those attending college as U.S. undergraduates in 2014 (American Association of Community Colleges [AACC], 2016). While the American public recognizes the need for an educated workforce, they also demand that their tax dollars be used wisely.

**Accountability.** The U.S. public wants greater accountability by asking that higher education institutions restructure their priorities and use resources more efficiently (Layzell, 2007; Polatajko, 2011; Robles, 1998). Polatajko (2011) indicates that legislatures in many states are beginning to look at changing the way they fund higher education as taxpayers resist funding models where positive outcomes are not achieved and question how their taxes are used. Many administrators agree that positive outcomes should be a measurement for funding but believe that it should only be one of the many
measurements used other than a reliance or “exclusive focus on credential completion and transfer rates” (Bailey, Jenkins, & Leinbach, 2005, p. 6). The National Conferences of State Legislatures (NCES), in their 2015 report, state that 32 states had moved to higher-education funding formulae based on performance and other specific outcomes like completions or graduations. As some states consider a move to performance-based funding models, both Layzell (2007) and Polatajko (2011) note that funding commitments may change depending on external influences like public perceptions of value, economic upheaval, or changing educational practices or trends. Additionally, Layzell (2007) and Polatajko (2011) report that some community college administrators do not believe their funding should rely solely on performance or outcomes. Because of open admission and access policies at community colleges, administrators believe that they have less effect on students’ retention leading to completion (Bailey et al., 2005) and, therefore, their funding sources and allocations should not be affected by these rates (Layzell, 2007; Polatajko, 2011). Bailey et al. (2005) believe there are three primary reasons for criticizing the use of graduation rates as a sole source to determine success. First, Bailey et al. (2005) state that students may have pre-existing “economic, social, and academic problems” (p. 7) when they enter that are beyond the community college’s influence. Second, not all students are pursuing credentials; instead, they may be seeking to enhance their skills and knowledge to further their employment opportunities (Bailey et al., 2005). These students successfully complete their educational objectives—for example, skill-builder coursework—but do not acquire degrees or certificates. Third, certain measurement indicators or calculated combinations of data do not take into account that many community college students are now attending multiple colleges in
their region or state and are successfully completing a credential program (Bailey et al., 2005). In this third situation, only one of the colleges may be awarding a credential but is using coursework from other colleges to fulfill the required credits needed to graduate. The other colleges do not receive acknowledgement or credit for the role they played in helping to fulfill those students’ credential requirements.

In addition to this, Baldwin (2014) states a concern that changing community colleges’ mission from one of open access to one of success may have unintended outcomes that redirect some students away from college entry, especially when success is used as a measurement to calculate funding allocation models. The open-access mission followed by community colleges accepts those students who are facing financial pressures, social and personal challenges, as well as those academically underprepared for college-level coursework. Of students who appear to have similar characteristics—“gender, ethnicity, parents’ level of education, socioeconomic,” (Vance, 2009, p. 55)—and academic skills at college entry, Vance’s (2009) research results suggest that those students who entered a two-year college were less likely to achieve academic success than their counterparts who entered four-year colleges. While four-year colleges and universities can be more selective in their admissions acceptances, thus improving their retention and graduation rates, community colleges’ mission remains one of providing access to all—even those who may require remediation prior to attempting college-level work (Bailey et al., 2005). Astin (1997) suggests that reporting actual outcomes and performance data as a measurement of accountability may be a “negative incentive for institutions to enroll underprepared students, since such students tend to lower the institution’s absolute level of outcome performance” (p. 656). Continuing this
distinction, Astin (1997) states that there should not be a comparison of implied value or quality between higher education institutions solely based on rates of outcomes like grades, time to completion and completion itself. If there is not a corresponding equalization of entering student characteristics, or “inputs,” (Astin, 1997, p.647) there is a potential disservice to those achievement rates reported by some higher educational institutions, in particular community colleges, where the entering student characteristics may include a greater number of those who require more remediation prior to starting college-level coursework.

**U.S. community colleges’ role.** With 47% of all U.S. undergraduates attending community college at some point in their educational career (AACC, 2016), community colleges have a longstanding history of providing an educational pathway to students seeking jobs and higher degree attainment (McKinney, 2011). In 2010, not long after President Obama stated the importance of community colleges in meeting his national completion agenda, six community college organizations (Table 3) representing 1200 community colleges nationally, came together to create a document that recognized and emphasized their support and “commitment to boost student completion by 50%” (American Association of Community Colleges [AACC], 2015, p. 1).

These six groups expanded on the outcomes expected from Obama’s goal of returning to the number-one ranking in the world by committing to produce a U.S. average of 50% college student completions by the year 2020 as well as increasing the quality of awards attained (AACC, 2015). However, these groups recognized that a culture shift was needed within the community colleges from one of pure access to one of access and completion.
Table 3.

*U.S. community college organizations committed to increase student completion rates*

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<tr>
<th>Organization Name</th>
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<tr>
<td>American Association of Community Colleges</td>
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<td>Association of Community College Trustees</td>
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<tr>
<td>National Institute for Staff and Organizational Development</td>
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<td>League for Innovation in the Community College</td>
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<td>Phi Theta Kappa</td>
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<td>Center for Community College Engagement</td>
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Martha Kanter (2011), during her tenure as U.S. Undersecretary of Education, indicated that approximately 44% of students entering community colleges needed remedial courses before being capable of college-level coursework. The U.S. community college system has historically evolved to expand from career and vocation training to provide educational opportunities to those who would not otherwise receive them: the “underserved, under-prepared, and under-represented” (McKinney, 2011, p. 22). Community colleges are asked to perform remediation functions while fulfilling other expectations, like career technical skill-building and developing educational pathways to four-year baccalaureate programs, for the populations they serve (Bamberger et al., 2012; Kanter, 2011). However, Kanter (2011) further states that the U.S. completion agenda needs restructuring at the K-12 levels to provide the quality and quantity of college-ready students for higher education’s role, especially for students seeking credentials from community colleges, to ensure a competitive population in the global marketplace.

**The California community college.** According to the California community college system master plan (California Community Colleges Chancellor’s Office [CCCCO], 2016b):
The California Community Colleges form the largest postsecondary educational system in the world. The system consists of 72 semi-autonomous districts encompassing 113 colleges, 77 off-campus centers and 23 district offices serving approximately 2.1 million students annually. As the most local of post-secondary educational institutions, California community colleges provide an affordable and quality education that often serves as a vehicle that strengthens both the local economy and the capacity of individuals (p. 6).

These community colleges respond to community requirements and workforce needs (CCCCO, 2013). With almost half of the nation’s undergraduate population educated by community colleges, they retain their identities as individual colleges but share common visions of access and providing services ("CC History," 2000; NCES, 2013). There is a current push by taxpayers and related funding mechanisms to have community colleges focus their education efforts on higher degree-seeking students (Layzell, 2007; Nettles & Millett, 2000). Currently, community colleges’ missions include open-access admission policies ("CC History," 2000; Layzell, 2007; Polatajko, 2011). For California, admission to enroll at its community colleges for the majority of students is guaranteed and applications are accepted throughout the year (CCCCO, 2013). Additionally, California community colleges’ missions encompass many outcomes and provide opportunities for full- and part-time students, those seeking transfer for four-year degrees and those hoping to expand their career knowledge and job skills (CCCCO, 2013; Shannon & Smith, 2006). However, many of these students are underprepared to successfully complete college-level coursework (Baldwin, 2014; Bulger & Watson, 2006) much less seek transfer admission at four-year institutions.
For the California community college system, with outcomes measured in academic year 2014-2015 for the student cohort entering college in academic year 2008-2009, only 28.6% of the cohort requiring English as Secondary Language (ESL) remediation completed at least one college-level course in the same discipline (California Community College Chancellor’s Office [CCC Chancellor], 2016a). For that same cohort, only 45.4% of those identified as needing English remediation and 32.7% requiring math remediation completed at least one college-level course in the same discipline (CCC Chancellor, 2016a) by the end of 2014-2015. These remedial courses were required before the student could advance to college-level courses requiring achievement of basic skill levels in speaking, understanding, and writing English or understanding mathematical concepts to pursue their ultimate educational or career goal.

Students attend community colleges for a variety of reasons. The two most common reasons identified for attendance at community college are to either attain a degree or certificate or secure sufficient credits to transfer to a four-year college to earn a baccalaureate degree (Business Higher Education Form & Emtec Solutions [BHEF], 2010). For each reason, completion of a higher education degree or certificate provides greater opportunity for viable employment that ultimately leads to entry into the middle-class economy (Carnevale et al., 2010; Kanter, 2011; Torraco & Hamilton, 2013). However, small numbers of these students actually persist to completion of their educational goal (AACC, 2015; BHEF, 2010; NCES, 2015). According to BHEF (2010) and other researchers (Astin, 1999; Berger & Braxton, 1998; Tinto, 1975), the reasons some students persist and others do not are varied.
Student Persistence in Higher Education

Because open-access admission is the primary mission of the community college (CCCCO, 2013), community colleges accept students who may not be ready for college-level coursework. Many of these students are considered part of the “New Majority students—displaced workers, single parents, immigrants, first generation or older” (Bulger & Watson, 2006, p.23) more than those referred to as traditional college-age students, aged 18 to 24 years old. Among all of these students, some may have no or limited higher education experience. This population looks to the community-college system to support them toward the successful completion of their education goals (Astin, 1999; Schwartz, 2010). Many in this group are underprepared for college-level coursework and college society and include those identified as at risk of not persisting to completion (Nettles & Millett, 2000; NCES, 2015; Pascarella & Terenzini, 2005). Two researchers, Beaudoin & Kumar (2012), identified students at risk of not persisting as those who “encounter academic challenges; do not engage socially in the campus community; or encounter financial challenges” (p. 8).

Tinto’s Model of Student Attrition. In 1975 and again when re-affirming and synthesizing his previous writings about persistence and institutional departure in 1988, Vincent Tinto suggested his “Stages of Institutional Departure” (Tinto, 1988, p. 439) had three components: separation, change or transition, and assimilation. Tinto (1988) asserts that each stage is relevant to a student’s persistence and ultimate decision to persist or depart. These decisions may have temporal boundaries, taking place throughout the duration of the student’s academic career.
In the first stage, separation, the student must leave what is comfortable and known for an unknown construct where he or she must assimilate into a new college community life and role within it (Tinto, 1988). For commuter students, those commuting from a home or other residence and not living in on-campus housing, this change may not be as stressful as it is for someone who is moving away from home. However, commuter students may experience a different type of separation anxiety because they retain their original community ties without ever fully integrating into their new college culture and lifestyle (Tinto, 1988). In either situation, the ability to successfully separate and assimilate will determine whether a student is likely to persist or depart.

With the second stage, a change caused by entering college is easier for those students for whom the cultural and social dynamics are not unlike those experienced before attending college (Tinto, 1988). Conversely, the greater the amount of change from previous behaviors, lifestyles, and social norms, the greater the amount of stress and anxiety students experience. Those impacted negatively by change may perceive a “sense of loss and bewilderment” (Tinto, 1988, p. 444) as their assimilation into college life has not fully developed allowing them to create new relationships and support systems. Without successful acceptance and development into this new social stratum, Tinto (1988) states, many students are unlikely to persist and may drop out before or by year’s end.

In the third stage and after successfully making it through stages one and two, Tinto (1988) identifies a phase of assimilation and integration into the college lifestyle and culture. However, for many students, this integration into their new college
community is something that they must develop on their own. Some students do not have the capacity to actively seek and advocate for entry into this new community. Without the ability to do so or if not provided as part of the college’s overarching support system, some students decide to leave and, therefore, do not persist with their educational goals.

**Bean’s Model of Student Attrition.** However, Bean (1981) believes Tinto’s student attrition model is but one piece of a more complex model composed of a variety of external and internal environmental influences. These influential variables often show a development of student intention where the intention, if developed and strong enough, may lead to attrition or lack of persistence. In Bean’s (1981) model, he believes there are four variables or reasons that students do not persist: “background variables, organizational variables, environmental variables, and attitudinal and outcomes variables” (Bean, 1981, p. 14), as these variables establish a basis for a student’s decision or strengthen an intention to depart.

Bean (1981) and others (Layzell, 2007; Polatajko, 2011) describe background variables as those over which colleges have no control. These variables are experiences, behaviors and attitudes developed before entry into college. While a college has not played a role in these pre-existing conditions, one combination of these background variables, high-school grades and test scores, is often cited as a predictor of student persistence (Bean, 1981).

Organizational variables are described as a combination of student engagements that help with the social and cultural integration of the student within the college structure (Bean, 1981). These variables include aspects of Tinto’s (1975, 1998, & 1993), Astin’s (1999) and other researchers’ (Berger & Braxton, 1998; Kelley-Hall, 2010) beliefs that a
student is more likely to persist if engaged and active in the college academic and social structures. These student interactions can be encouraged by the college and may be varied to include both formal and informal contact with faculty, staff, administrators, and other students (Bean, 1981; Bean & Eaton, 2004).

Environmental variables are described by Bean (1981) as those that happen while the student is attending college but not directly as a result of attending college. These variables include those life events that impact college attendance. Examples of these variables include employment or transfer opportunities, family influence on where the student attends college, a change in the student’s program of study requiring a transfer to another institution, family responsibilities, and/or economic pressures (Bean, 1981). While the college can provide support when these life pressures provide reasons for a student’s increased intention to depart, the college may not be aware of the student’s intentions until it is too late to act.

Attitudinal variables are those that are “more subjective” (Bean, 1981, p. 17) and may have more influence on a student’s decision to depart or not persist at college. These student attitudes are created from the student perspective and based on both background and organizational variables that influence students’ “intent to depart” (Bean, 1981, p. 18). The student’s intention to depart may be the strongest indicator of a student deciding to drop out or not persist. However, this intention may be difficult for a college to identify and measure without the college formally and informally engaging the student.

**Student engagement and involvement.** Tinto (1975, 1998, & 1993) provided a model of the social and economic impacts of students dropping out of college. Other researchers (Astin, 1999; Kimbark, 2015; Pascarella & Terenzini, 2005) elaborate on
Tinto’s initial theory and suggest both student engagement and involvement while attending college play a significant role in persistence and retention. Engagement was identified from the simple to the more complex—from making friends and joining social activities on campus to engaging with formal study groups and structured tutoring sessions (Webber, Krylow, & Zhang, 2013). Webber et al. (2013) agreed that the more involved the student was in the college community, the more likely that the student would persist and succeed both academically and socially.

Berger and Braxton (1998) reviewed Tinto’s seminal 1975 model in conjunction with later models and theories of student persistence or intent to depart. Of Tinto’s (1975) 13 proposed reasons for student attrition, Berger and Braxton (1998) believe only 4 are widely supported. Berger and Braxton (1998) summarize these four:

Student entry characteristics affect the level of initial commitment to the institution. The initial level of commitment to the institution also influences the subsequent level of commitment to the institution. This subsequent level of initial commitment is also positively affected by the extent of a student’s integration into the social communities of the college. The greater the level of subsequent commitment to the institution, the greater the likelihood of student persistence in college (p104).

Some of this initial commitment is created prior to the student entering college. However, from the first points of interaction with the students, in the form of marketing and recruitment efforts, to personal contact during the admission process, colleges influence and build higher levels of student commitment. Additional commitment continues to grow if positive engagements are made in the classroom and through
services and practices that are based in the culture of the organization (Berger & Braxton, 1998). Without adequate positive interactions, especially in the first months to year of college entry, there is a greater likelihood of students’ not persisting and intention to depart.

**Students at risk of not persisting.** Community colleges attract a diverse population of students ranging from what is considered traditional-aged 18-to-24-year-old college-goers to the older returning adult, aged 25 years or more, who may have some or no college experience. Each of these students brings with them at college entry a unique history of education and experience—some positive, some negative—that may affect their intention to stay in school or persist (Bergman, Gross, Berry, & Shuck, 2014). For traditional-aged students, their demographic information and background as well as pre-college experiences provide a different set of factors that may influence whether these students will persist. These factors include high-school cumulative grade point averages, “high school rank, standardized test scores, college prep curriculum,” (Bergman et al., 2014, p. 91) as well as social integration while in high school. For older returning adult students, some characteristics that may indicate persistence are “socioeconomic status, race/ethnicity, age, gender, marital status (including number of children), total previous college credit earned and goal commitment” (Bergman et al., 2014, p. 91). Bulger and Watson (2006) state that the at-risk student definition, for both traditional-aged and returning adult learners, may be expanded to include lack of sufficient technology knowledge and aptitude, especially when trying to successfully complete online course offerings. Bulger and Watson (2006) determined by review of their research results that those students who entered college expecting to complete their
educational goal and receive a credential were most likely to persist. This is in line with the conclusions drawn by Berger and Braxton (1998), recognizing that commitment to the intent of persistence is a strong motivator and factor in actually completing the student’s educational goal. While other factors, like campus culture, support services, financial capability to afford college, and family and friends providing emotional support and encouragement, were identified as important to achieve student persistence, the intention to pursue and complete an educational goal had more of a positive impact on student persistence (Bergman et al., 2014). However, providing a positive college environment along with accompanying support services and practices increased students’ willingness to persist (Astin, 1999; Bean & Eaton, 2004; Kelley-Hall, 2010; Tinto, 1975, 1993 & 2004).

Community colleges’ roles and responsibilities. Community colleges use a broad-based set of engagement and involvement strategies and practices to meet the unique academic and social needs of their student population (Bailey & Alfonso, 2005; Schwartz, 2010; Zhang et al., 2014). While some researchers (Astin, 1999; Polatajko, 2011; Porchea et al., 2010; Schwartz, 2010) state community colleges cannot influence student life experiences prior to entry, Schwartz (2010) states that community colleges can present experiences and encourage engagement while students are in attendance. Schwartz (2010) continues to reflect that positive experiences in the form of institutional behaviors and practices may influence the students’ willingness to stay in college and complete their academic goals. Community colleges often discover a student has dropped out after the event occurs and, many times, without an intervention strategy convened (Beaudoin & Kumar, 2012). Some of the support provided and considered
beneficial by researchers includes counseling and academic advising (Zhang et al., 2014), tutoring in reading, writing, and math, and helping them advance in technological skills and capabilities needed in 21st-century higher education institutions and workplaces (Bulger & Watson, 2006).

According to Kelley-Hall (2010), student support services create social and academic experiences that provide students with opportunities to become involved in campus activities. Students engaged in campus life interact with other students, faculty and staff. These student interactions generated a sense of belonging and well-being “by creating an environment connected to involvement and achievement” (Kelley-Hall, 2010, p. 148). However, many community colleges may not have the needed funding and staff resources to effectively scale-up these student support services that acclimate a student to college life. Webber et al. (2013) believe student engagement and involvement in both curricular and co-curricular activities are necessary to contribute to student success. Types of activities under the general heading of student engagement may include making new friends, joining study groups, and enlisting in student clubs. These activities help students become acclimated to the college and create a sense of belonging. Webber et al. (2013) also concluded that students who actively prepared (studying, assignment completions) for class received higher grades and were more satisfied with their college experience.

**Student Course Completions**

Various researchers (Astin, 1997; Astin & Oseguera, 2005; Bean & Eaton, 2001; Bergman, Gross, Berry, & Shuck, 2014; Nodine, Venezia, & Bracco, 2011; Tinto, 1993, 2004; Whalen, Saunders, & Shelley, 2009-2010) have written about student degree and
credential completions. Significant data exist at federal, state and private organizations (AACC, 2015; ACT, 2015; CCC Chancellor, 2016a; NCES, 2015; OECD, 2014; USED, 2015) that identify terminal degree completions as a leading measure of student completion or success. Astin (1997) believes that student course completions and degree attainments are key indicators of institutional effectiveness. However, in increasing student course completions, the numbers of students who receive a degree, certificate or transfer to further their credentials will also increase (Yaghmaee, 2013). Course completions are seen by Goldrick-Rab (2010) as “intermediate indicators or milestones” (p. 440) and may reflect a student’s overall progress. For community colleges, Goldrick-Rab (2010) states that when enrollment rises, students compete for limited college resources and completion rates decrease. Because current California funding of community colleges is largely based on enrollment numbers, colleges have not, until recently, emphasized completions (Goldrick-Rab, 2010).

Adelman (1999) suggests that student self-reports of status, i.e. full- or part-time, are not always accurate. Students still include all courses attempted rather than the “ratio of drops/withdrawals/incompletes to total courses attempted” (Adelman, 1999, p. x). Adelman’s (2005) data (Table 4) suggests, for the 51.7% of those 1992 twelfth-graders who attended community college only and earned 10 or fewer credits (including 0 credits), 17% of the students who were in short-term vocational programs may have completed their educational goals. Adelman (2005) further suggests that lack of course completions leading to credential attainment is, in part, a failure by the student to acquire sufficient skills to “negotiate the environment” (p. 52) at the community college.
Table 4.

Of 1992 twelfth-graders who attended a community college at any time, attending community college only, earning ten or fewer credits (including zero credits) – breakdown of 51% who attended community college only

<table>
<thead>
<tr>
<th>Percentage</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>29%</td>
<td>Carried records of course work that were overwhelmingly remedial, hence earned few or no additive credits</td>
</tr>
<tr>
<td>17%</td>
<td>Were in short-term vocational programs</td>
</tr>
<tr>
<td>45%</td>
<td>Failed too many courses to accumulate more than ten credits</td>
</tr>
<tr>
<td>9%</td>
<td>Continuing education students (no credits)</td>
</tr>
</tbody>
</table>

Note: Data extracted from Adelman (2005) – Table 21, p. 53.

In 2006, Adelman continued data analysis of his original cohort of 1992 twelfth-graders and determined:

- “Withdrawing from or repeating 20% or more of courses decreases the probability of earning a bachelor’s degree by nearly half!!
- Remaining continuously enrolled increases the probability of degree completion by 43.4%” (p. 74)

Adelman (2006) found that allowing “negative momentum” (p. 74) in the first year of study through course withdrawals, with or without penalty, is not conducive to completion. Adelman (2006) argues that the first year is critical to achieving student behaviors by providing consistent academic advising, checking-in points with faculty and staff, multiple measures for assessment, and, for some students, a decreased credit load in the first year.

Goldrick-Rab (2010) indicated a “positive relationship between the availability of resources per student” (p. 443) and completion rates. Yaghmaee (2013) found that “tenured or tenure-track faculty is the only variable that positively and significantly correlated with the completion rate” (p. 113). Jong & Krenkel (2013) believe that course
completion rate improvements are directly tied to faculty engagement with students in the classroom. Additionally, Jong & Krenkel (2013) believe the recruitment and hiring process helps determine how a faculty approaches engagement and understands the importance of student course completions. Yaghmaee (2013) stated that in the period between 2007 and 2013, when state budget cuts decreased the ratio of full-time faculty to part-time faculty, the California community college scorecards reflect student completion rates that dropped from 52.3% to 49.2%, respectively. Yaghmaee (2013) reports that his principal finding “suggests that community college completion rates increase as the proportion of full-time faculty increases” (p. 115), but adds that these increased rates may occur only if the faculty engaged with students. However, Yaghmaee (2013) also suggested that when one looks at individual districts’ or colleges’ overall human resources compared to faculty size, non-instructional employees providing supplemental services (counseling, advising, tutoring, financial aid, administrative support and others) may positively increase student completion rates.

Administrators’ Roles

The California community college administrator’s role is to create, coordinate and oversee comprehensive, broad-based services in support of student retention and completion (Akoma, 2012; Smith, 2013). These services provide opportunities for students to engage in the community-college experience through academic and social interactions with other students, faculty, and staff (Akoma, 2012; Callery, 2012; Dorsey, 2014; Webber et al., 2013). As a result of that involvement, Webber et al. (2013) believe that students will stay in school and complete their academic objectives. However, administrators must balance those practices leading to student retention and success with
individual student academic and social needs (Akoma, 2012). Comprehensive data analyses identifying at-risk student behaviors help an administrator direct promising practices and services to these students to keep them in school (Beaudoin & Kumar, 2012; Callery, 2012; Delen, 2011-12; Dorsey, 2014).

Administrators oversee some of the most complex parts of the community college organization (Dorsey, 2014; Kuk & Banning, 2009). The departments, divisions, and areas responsive to external and internal pressures created from expectations of student success typically are under these educational administrators’ jurisdiction and range from student government to counseling (Kuk & Banning, 2009) and instructional faculty. Kuk & Banning (2009) state that administrators tend to have more direct reports from those who oversee the practices and services that help at-risk students. While organizational structures differ from one college to the next, the role of the administrator is to assist the institution toward its mission and goals of student success (Kuk & Banning, 2009).

Whalen, Saunders, and Shelley (2009-2010) found in their research that the implementation of learning communities greatly increased one-year retention rates as it was a means “to assist students with both academic and social engagement at the institution” (p. 425). For those administrators at institutions who identified students potentially at risk of not persisting by using existing data like low grades in the entry term, poor attendance in class, and significantly, insufficient financial aid, Whalen et al. (2009-2010) determined that administrators could use this information to create or enhance policies and practices to support academic success and engagement. Though research by Astin & Oseguera (2005) suggests that persistence is “a complex phenomenon that can be affected by variety of student pre-college characteristics,
environmental contingencies, and institutional characteristics” (p262), administrators have used these broad-based data resources to increase student retention and persistence practices in the first year that are an institutional fit for the students they serve. After the first year, additional variables and indicators, like good grades, consistent attendance and motivation, identify those students with or without intentions to complete their educational goals (Astin & Oseguera, 2005; Whalen et al., 2009-2010). Each group of students need support practices throughout their educational journey.

**Promising practices.** Tinto’s (1975, 1988, & 1993) research suggests creating student support programs and institutional practices that increase academic and social engagement and integration while helping students separate from their previous social and academic experiences and transition to life at college. Common successful programs include learning communities, college orientation sessions, and cohort-driven social and academic activities. While administrators are interested in increasing their institutions’ overall completion numbers and retention rates, Bean and Eaton (2001) state that administrators need to know the psychology behind why these types of programs and practices work and why some they thought would work do not. As identified by Bean and Eaton (2001), student support programs should incorporate practices that increase the confidence of students in four areas by building beliefs that students are: (1) socially effective; (2) academically effective; (3) in control of their outcomes; and (4) have developed “coping skills and [are] motivated to approach academic and social challenges” (Bean & Eaton, 2001, p. 85). Based on the findings of Bergman et al. (2014), “as a student felt more strongly that an institution was responsive to his or her needs, the odds of persisting increase” (p. 98).
**Intrusive services.** The Center for Community College Student Engagement (CCCSE) promoted their 2004 findings that engagement should be inescapable as part of common institutional practice available to all students by creating structured educational pathways (Center for Community College Student Engagement [CCCSE], 2014). Built into these pathways are intrusive services that force engagement. CCCSE (2014) identifies high-impact practices as those that have a high level of student engagement and that also have a correspondingly high level of student persistence and completion. As part of CCCSE’s (2014) findings, they identified nine high-impact practices: Orientations to give students information on support programs and academic services the institution offers; accelerated developmental coursework that more quickly moves a student to college-level courses; a first-year experience that mixes students into both in-class and out-of-class activities; a student success course that provides more formal information on how to navigate and successfully complete their educational goals; creating learning communities within linked courses so that students can provide each other with support; advising services to create educational plans; experiential learning opportunities to provide hands-on experience with content; tutoring through a variety of modalities (online, in person, in groups); and supplemental instruction provided as an adjunct course to a portion of the class in a more structured format.

**Limiting options.** Similar and as part of a pathways concept, CCCSE (2014) suggests that limiting options to students may help them persist. Many California community colleges offer dozens to hundreds of certificates and degrees. Combined with these credential offerings are the multitudes of courses that support them. With so many options available to them, students may “experience anxiety and frustration…and, as a
result, are more likely either to make a poor decision or to retreat from the situation” (CCCSE, 2014, p. 3). By creating structured pathways and purposefully limiting options, administrators provide students a clearer path to both persist and succeed to completion. Jenkins and Cho (2013) believe guided pathways allow students to not only achieve their educational goal but accelerate their completion of it. However, Jenkins and Cho (2013) state that there are three elements that must exist in guided pathways at community colleges:

1. Create a clear set of suggested sequential courses. While limiting course options, students still have the ability to customize the plan with alternative courses to minimize time to completion. Minimizing options keeps the end goal in sight and allows for a more successful pathway to either a career or an education objective.

2. All paths lead to a program of study. An undecided student or one who requires remediation to place into college-level courses can follow a prescribed general-education curriculum that will support future educational or career goals. The guided pathway allows for ongoing social and academic engagement while the students are researching their best-fit pathway.

3. Advising and support. Continued engagement through identified progress points and intervention strategies keep students on track for completion and complement persistence practices. Even those students who appear on-track and academically successful need feedback and support. The most successful of these practices are embedded into the pathways and provided to all students, not just those at risk of not persisting.
When administrators limited choices and provided defined, structured, and consistently communicated pathways with embedded engagement opportunities to community college students, Jenkins and Cho (2015) found students were less anxious, less frustrated, and more focused on their intended achievements and goals. However, Jenkins and Cho (2015) suggested that these pathways, to have successful outcomes, needed institutional leaders who create an environment of shared knowledge and information that collaboratively leads to the development of strategic, guided pathways. Smith (2013) agreed that collaborations by all members of a community college, especially faculty advisers, using shared data and knowledge, allowed for creation of intrusive support services that engaged students and kept them on their structured pathway to completion.

Knowledge Mobilization

Knowledge mobilization (KMb) has been described as a convergence between research and evidence toward changing policy and practice (Levin, 2013). By using the term mobilization, Levin (2013) “indicates that this work requires specific effort, over time, working with others, and involves much more than telling people about research findings” (p. 2). Levin (2013) further suggests that KMb is an interactive multidirectional process involving people reviewing data-derived information and relating it to institutional practices. According to Sa, Li, & Faubert (2011), college and university faculty and staff have overall positive views toward evidence and information driving practices and policy. However, Sa et al. (2011) report that while there is support, there are also perceived or actual barriers to its implementation. The barriers identified included lack of time, lack of measurable outcomes established, lack of research and
technological resources, and too many diverse initiatives with competing data needs (Sa et al., 2011).

**Data sources.** Colleges have many collection points for and resources of data (Bachler, 2013; Dorsey, 2014; Macfadyen & Dawson, 2009). These repositories include their student information, learning management, institutional research and other systems. Additionally, external sources of data from federal, state, and municipal repositories may be extracted to provide a picture unique to the population a college serves. These data can include regional and national employment trends, economic needs, cultural diversity, genders and age distributions. Multiple state and federal initiatives suggest a move to data-driven decision-making to identify intervention strategies to prevent student attrition (Beaudoin & Kumar, 2012; NCSL, 2015). Knowing the customer base served helps to identify appropriate resources.

**Big data.** Given twenty-first-century technological advances combined with a variety of data, more pressures and accountability are placed on administrators to use the data available to them to make informed decisions. Data-driven decision-making is often described as “the practice of basing decisions on the analysis of data rather than purely on intuition” (Provost & Fawcett, 2013, p. 53). Conversely, the term big data, for this research, is defined as a dataset so large that it either needs or requires its own technology to handle it and/or processing data to support data-mining and similar activities (Provost & Fawcett, 2013). The best example of large amounts of data for higher education institutions are student records. According to Picciano (2012), these detailed student records could be used “to study patterns of student performance over time, usually from one semester to another or from one year to another” (p. 12). Each student has multiple
courses; each student has a grade or notation for each course. The data continues to build over time and is magnified when other sets of data, e.g., learning management systems, are added to it (Picciano, 2012). Just as in business fields outside of education, higher education is utilizing its own big data to obtain a competitive advantage related to economic accountability with its funding sources while optimizing information on its students to identify practices to help them persist and complete their educational objectives.

**Predictive Modeling Software**

Historic data are available to review when a student drops out of college. Additionally, other data are available that may identify certain behavioral and academic predictors common among student populations at risk of not persisting. These historic data, when combined and analyzed with current data reflecting student behavior and activity, model and identify the possibility of an event before it happens (Essa & Ayad, 2012; Macfadyen & Dawson, 2009; Porchea et al., 2010). Predictive modeling software takes the collected data from these sources and analyzes it to predict possible student behaviors (Beaudoin & Kumar, 2012; Dorsey, 2014; Reyes, 2015) to “provide proactive outreach to students using systematic and sustainable methods” (Smith, Lange & Huston, 2012, p. 51). This type of data modeling can predict college student behaviors as a collection of items that lead to a particular outcome (dropping out) (Bailey & Alfonso, 2005; Beaudoin & Kumar, 2012). However, if the data used to model or predict behaviors and outcomes are incomplete or are not significant predictors of course completion, the ability to predict outcomes may be limited. Predictive modeling can identify positive outcomes, such as staying in college, as well as determinations that
would indicate at-risk behaviors (Dorsey, 2014). The results of this modeling may then be used to provide interventions to prevent dropping out (Bailey & Alfonso, 2005; Beaudoin & Kumar, 2012; Dorsey, 2014).

Smith et al. (2012) suggest that the quantity of data collected and analyzed, from the beginning of a course until its end, allowed for greater accuracy to predict student outcomes and successful course completions. In particular, Smith et al. (2012) suggest that learning management system (LMS) data, in combination with other student data collected from various sources, provide sufficient information to accurately predict course completion rates. LMS information systems are used in online and in-person classrooms to provide students around-the-clock access to course content, homework assignments, quizzes, and tests. The LMS helps manage “interactive communication with students via messages, forums and surveys” (Naveh, Tubin & Pliskin, 2010, p.127). By accumulating detailed information on student activity in the course, these LMS systems act as a data repository of student engagement by tracking the instances of student access and amount of time spent in the LMS. Milliron, Malcolm & Kil (2014) suggest predictive modeling is a tool used to “visualize data, operationalize interventions and outreach, choose modalities, provide real-time feedback, and test the timing of interventions and outreach” (p. 81). Additionally, Milliron et al. (2014) warn of “unintended consequences” (p. 81) when using predictive modeling inappropriately—feedback communicated to a student in such a way as to predispose the student to failure.

Some researchers (Calvert, 2014; Denley, 2014) believe that certain errors and tolerances in the model may limit the ability to accurately predict outcomes. Some of the drawbacks identified were:
• Insufficient data – data sets weren’t large enough
• Human behavior – changing behaviors that impact predictions weren’t often anticipated by computer algorithms
• Timing – a model may be successful now but as behaviors change, the model would need updating
• Inaccurate or missing data on key variables
• Model assumptions may be invalid
• Other random prediction errors (Calvert, 2014; “Predictive Analysis Drawbacks,” 2017)

Calvert (2014) further stated: “Predictive modeling cannot determine exactly that probability [of successful completion] but it can estimate it” (p. 170). Denley (2014) believed a “model that used the past to influence the future” (p. 66) had the potential to perpetuate negative stereotypes and suggests that models should be built to “safeguard against such a phenomena” (p.66).

While many community colleges lack comprehensive institutional research departments and staff, data are available for collection and analysis (Polatajko, 2011). Although predictive modeling is a useful decision-making tool to identify those students potentially at risk of not completing courses, the data analysis must be accessible, reliable, usable, and understandable to benefit community college administrators (Dorsey, 2014; Marsh et al., 2006). Using these predictive models to make data-driven decisions, administrators may then create, enhance or revise policies and practices related to intervention strategies that keep students in school (Bachler, 2013; Delen, 2011-12; Keys, 2013; Whalen, Saunders, & Shelley, 2009-2010). In particular, community college
administrators are turning to data-identified models to make decisions to identify and concentrate efforts to students at risk of non-completion (Delen, 2011-12; Whalen et al., 2009-2010). The administrators’ evolving role is to ensure the policies, procedures, programs, and services offered to students at risk of non-completion are viable, timely, and appropriate (Kuk & Banning, 2009; Dorsey, 2014).

**Administrators Use of Data**

As community college administrators look more closely at data to improve processes that support students staying in school, Callery (2012) suggests encouraging a general culture of inquiry and evidence throughout the institution that assesses and re-assesses program information for viability, performance, and usefulness. Dorsey (2014) adds that community colleges already collect and store assorted and diverse data on their students, but little is done with that data as a means to make institutional improvements to increase strategic outcomes like retention and persistence rates of its students. In a report from the Lumina Foundation, Dowd (2005, p.1) states that “accountability policies require institutions to report data that are never actually used” and suggests that college administrators continually question, analyze, and engage in professional dialogues about their data to achieve change and improvements in student success. Through administrators’ moving to data-driven decision-making using predictive modeling tools, students may be provided individualized intervention strategies unique to their personal needs and experiences (Bachler, 2013; Beaudoin & Kumar, 2012; Callery, 2012; Essa & Ayad, 2012).

Creating appropriate intervention strategies requires an understanding of the integration of various data that suggest appropriate policies and practices that lead to
student persistence (Whalen et al., 2009-2010). Baldwin (2014) suggests that administrators “collect and use data to inform a continuous improvement process” (p. 4). Although predictive modeling is a useful decision-making tool to identify those students potentially at-risk, the data analysis must be accessible, reliable, usable, and understandable to benefit community college administrators (Dorsey, 2014; Marsh et al., 2006). Using these predictive models to make data-driven decisions, administrators may then create, enhance or revise policies and practices related to intervention strategies that keep students in school (Bachler, 2013; Delen, 2011-12; Keys, 2013; Whalen, Saunders, & Shelley, 2009-2010).

Some California community colleges have implemented predictive-modeling software to help administrators forecast and identify those students at risk of not persisting toward their educational goals (Bachler, 2013; Callery, 2012; Delen, 2011-12; Dorsey, 2014). Callery (2012) states “community college leaders must assume the role of change agents to manage the transformation of their organizations to fully integrate strategic planning initiatives, such as data-driven decision-making to enhance institutional effectiveness” (p. 216). Callery (2012) further suggests that additional study is needed to determine if there are shared data-analytic approaches used by community college administrators “to manage college operations, services and academic programs” (p. 241). Ewen’s (2015) research noted that there was a “general lack of clarity related to the use of data with the greatest potential to impact the student learning, success, and degree completion.” (p. 96). For administrators at these California community colleges who have access to predictive-modeling data, it is unclear how they make use of the data available to them to make changes to those policies, procedures, programs or services.
that affect student retention and completion (Alt, 2012; Callery, 2012; Dorsey, 2014; Ewen, 2015; Smith, 2013). Additionally, the exact nature of those changes is unknown.

**Actionable knowledge.** College administrators hope to increase student retention by using available data and forecasting tools to identify those students most at risk of not persisting in their studies and help them before they decide to drop. In particular, community college administrators are turning to data-identified models to make decisions to identify and concentrate efforts to students at risk of non-completion (Delen, 2011-12; Whalen et al., 2009-2010). Marsh, Pane, & Hamilton (2006) suggest there are two primary types of decisions that come from “actionable knowledge”—“those using data to inform, identify, or clarify (e.g., identifying goals or needs) and those that entail using data to act (e.g., changing curriculum, reallocating resources” (p. 3). The administrators’ evolving role is to ensure the policies, procedures, programs, and services offered to students at risk of not persisting are viable, timely, and appropriate (Kuk & Banning, 2009; Dorsey, 2014).

However, it is unclear how administrators use the data available to them to make changes to those policies, procedures, programs or services that affect student persistence and completion (Callery, 2012; Dorsey, 2014; Smith 2013). Additionally, the exact nature of those changes is unknown (Callery, 2012; Dorsey, 2014). Callery (2012) suggests that research is needed to identify “data infrastructure design considerations” (p. 241) that may help create more comprehensive data-mining and analytic reports to support improved practices toward student persistence and completion. Another researcher (Grodzicki, 2014) suggests that further research is needed to provide a “more
comprehensive analysis of the use of systematic evidence in reforming educational
practices” (p. 141).

Summary

This review of the literature and research focused on the evolution over time of
data use by administrators to effect change in patterns of student course completion in
higher education. By using multiple sources of actionable knowledge as provided by data
analyses and predictive modeling software, California community college administrators
have new resources and tools to inform decisions related to policy, process, practice and
service for students identified as not likely to persist toward their educational goals.

Data collection, analysis and review play an important role in data-driven
decision-making by administrators interested in student retention at California
community colleges (Callery, 2012). Dorsey (2014) suggests that most community
college administrators currently use data to only review enrollment and budgets.
However, there is no clear understanding of how administrators use predictive modeling
to identify and make institutional changes that may lead to improved student retention
(Dorsey, 2014; Callery, 2012; Ewen, 2015). Callery (2012), Dorsey (2014), and Ewen
(2015) suggest that further research is needed to build “a culture of evidence to support
student success” (Dorsey, 2014). By pursuing this research, a better understanding of
data-driven decisions, specifically data provided by predictive-modeling software, as
used by administrators to increase student course completions at California community
colleges was explored.
Synthesis Matrix

A synthesis matrix (Appendix A) was developed to assist the researcher to determine, define, and synthesize the major components of the research.
CHAPTER III: METHODOLOGY

This chapter explains the methodology used in this study and includes a general overview of the topics addressed. This chapter also includes the purpose statement and corresponding research questions. Further, this chapter addresses the research design, identifies the population and sample, and describes the instrumentation and data-collection process. After data collection, the data-analysis section of this chapter describes how data was analyzed. Limitations of the study are identified and a chapter summary is provided.

**Purpose Statement**

The purpose of this case study was to determine the impact of utilizing predictive modeling to improve successful course completion rates for at-risk students at California community colleges. A secondary purpose of the study was to identify factors of predictive modeling having the most importance for improving successful course completion rates for at-risk students as perceived by California community college administrators.

**Research Questions**

RQ1: What was the impact of utilizing predictive modeling to improve successful course completion rates for at-risk students at California community colleges?

RQ2: What factors of predictive modeling have the most importance for improving successful course completion rates for at-risk students as perceived by California community college administrators?
Research Design

This study utilized a case study (Figure 3) research design incorporating interviews and review of archival records from colleges within two California community college districts. Each college sampled represented one case study. By combining qualitative and quantitative methods, this study enhanced the strengths of each design and mitigated the weaknesses to provide “a stronger understanding of the problem or question than either by itself” (Creswell, 2014, p. 215). Patton (2015) suggests the data resulting from a blend of design methods provide “cross-data validity checks” (p. 316).

Figure 3. Adapted representation of an embedded multiple case study design (Yin, R.K., 2012, Figure 1.1).

A case-study design allowed the collection of data to ascertain those factors deemed most important on improving intended outcomes, especially course completion rates, as
perceived by California community college administrators’ utilization of predictive modeling software. This methodology allowed the researcher to first collect and review archival data to “develop quantitative data…to explore relationships found in the qualitative data” (McMillan & Schumacher, 2010, p. 402).

Yin (2012) states that “leaders of organizations frequently serve as the subjects of case studies” (p.51). These leaders are selected for inclusion in studies because they “are presumed to have followed some courses of action, made some decisions, or exerted some influence that offers important lessons to be learned” (Yin, 2012, p. 51). Yin further states that the importance of multiple-case studies is that the “analytic conclusions independently arising from two cases, as with two experiments, are more powerful than those coming from a single case (or a single experiment) alone” (Yin, 2012, p. 133-34). The review and analyses were of multiple cases involving five CSSOs’ interview transcripts, along with archival data and related documents.

Yin (2014) states that case studies are appropriate to use when no constraints are imposed over participants’ behavior and the study is focused on contemporary events. A case-study research method of inquiry allows the researcher to explore the human element, experience, and perspective to influence the direction of the study and uses open-ended questions that explore the problem studied (Patton, 2015). Yin (2014) further states that “the case study’s unique strength is its ability to deal with a full variety of evidence—documents, artifacts, interviews, and observations” (p. 12). A case-study approach is appropriate when it attempts to “illuminate a decision or set of decisions: why they were taken, how they were implemented, and with what result (Schramm, 1971)” (Yin, 2014, p. 15).
The case-study design allows the researcher to collect diverse types of data that help determine the impact on course completion rates by those administrators who use predictive modeling. With the data collected, the nature of the administrator decisions and changes made to practices that influence student course completions are clarified. The administrators then provide, through in-person interviews with the researcher, their personal reflections and perceptions of those factors having the most importance for improvement of course completion rates by using predictive modeling. While a case study may “include, and even be limited to, quantitative evidence” (Yin, 2014, p. 19), this study will look at qualitative evidence in the form of interviews and a review of documents and artifacts. The “investigator usually acts as an observer in the setting that is being studied, either as the interviewer, the observer, or the person who studies artifacts and documents (McMillan & Schumacher, 2010, p. 322).”

Archival data, sometimes referred to as secondary data, derived from the CCCCO Management Information Systems (MIS) Data Mart were identified as supporting evidence for successful course completions rates at California community colleges and districts, including those participating in this study. This quantitative data allows for review and analysis (McMillan & Schumacher, 2010) of student course completions to answer the research questions. MacMillan and Schumacher (2010) suggest that “secondary data can provide a context for interpreting the findings that result from primary data collection efforts” (p. 246).

**Archival Data**

Quantitative research has been defined as “a method of inquiry for describing as well as elucidating the relationships among variables” (Martinez, 2007, p. 73). Analyses
were performed on data collected into the Data Mart for academic years 2013-14 through 2015-16 from the California community colleges and districts. Some considerations for using archival data were that the dataset contained the variables needed to calculate reported course completions by district and included the sample population that met the criteria of the research questions. Additional considerations met were data accessibility, technical applications and assistance available. California community colleges regularly report student data to the state chancellor’s office. These public community college repository data are compared cumulatively and disaggregated by age, gender, ethnicity, and other indicators to determine answers to the research questions. This study will review existing and disaggregated data, “secondary data analysis,” (McMillan & Schumacher, 2010, p. 242) from the Data Mart to pull reported course completion rates from the sample districts.

**Interviews**

Qualitative research methods allow the human element, experience and perspective to influence the direction of the study (Patton, 2015). The method uses open-ended questions that explore the problem studied. This approach does not predict outcomes and, therefore, does not require a hypothesis. By using this qualitative method, the researcher may add additional information that provides substance and humanity to the numbers. The data are textual and collected through interviews and observations using a variety of media. As an observer, the researcher does not influence the behaviors and allows those being studied to act naturally in their normal surroundings and environment (Patton, 2015).
Documents

Patton (2015) suggests that the review of artifacts can provide an additional context and perspective to qualitative research. Artifacts can take different forms and provide traces of material to add to interview transcripts. Revelations from these artifacts may include background and history or goals and objectives to help answer, in part, the research questions. Potential artifacts include institutional reports showing course-completion metrics, public-meeting minutes from trustee meetings, and web sites. Artifacts were used as supporting documents only if they directly addressed and answered the research questions. Administrators were asked to consider providing artifacts to the researcher or directing the researcher to potential artifacts on their public sites for inclusion in this study. Those artifacts collected and used were entered into NVivo software for inclusion with themes to produce additional data tables for analysis.

Population

McMillan and Schumacher (2010) describe a target population as “the total group to which results can be generalized” (p. 129). Within the 113 California community colleges, there are 2,153 (Figure 3) employees categorized as administrators (CCCCO, 2016). The target population identified for this study was California community college administrators holding the position of chief student services officer (CSSO). CSSOs preside over student services departments and areas that are often non-instructional in nature but are tasked with outcomes associated with student success, in particular those services that assist students with persistence and course completions. “The CCCCO provides more than $590 million annually in categorical and grant funds that help
colleges provide support services across the campus and supplemental services for special populations” (CCCO Student Services Division website, 2017).

These support services rely on the oversight of the CSSO. The approximate number of employees with these titles is 113 if each college has a unique employee assigned to each CSSO position. This number assumes there are no vacancies and recognizes that some colleges may have one combined position to cover responsibilities and functions of the CSSO and other administrative areas. Within this target population, additional criteria included a college or district purchase of the Civitas Learning, Inc. (Civitas) predictive-modeling software, combined with product exposure and/or training. The sample population includes those California community college districts known (as provided by the vendor, Civitas) to have purchased or implemented a predictive-modeling software program, Civitas Illume for Students. Through this purchase and exposure to the implementation needs of this software solution, the CSSOs at the colleges within each district were considered knowledgeable about potential uses of predictive-modeling data.

**Sample**

A sample population is defined as “the group of subjects or participants from whom the data are collected” (McMillan & Schumacher, 2010, p. 129). A purposeful sampling strategy, “selecting subjects with certain characteristics…that are representative or informative about the topic of interest” (McMillan & Schumacher, 2010, p. 138), was used by selecting “multiple cases of a phenomenon for the purpose of generating generalizable findings that can be used to inform changes in practices, programs, and policies” (Patton, 2015, p. 270). McMillan and Schumacher (2010) state that the sites
selected should identify people involved in the phenomenon and be ones where
“viewpoints or actions are likely present and can be studied” (p. 326). This study focuses
on “a representative sample” (Roberts, 2010, p. 148) of CSSOs in California community
college districts that acquired and/or implemented data-analytic software for the purpose
of predictive modeling of their student populations.

Because there is not a common repository listing colleges’ utilization of
predictive modeling or supplemental software, the researcher relied on one vendor,
Civitas Learning, Inc. (Civitas), of a known predictive modeling software to provide a
listing of those California community college districts that purchased the Civitas Illume
for Students (Illume) predictive modeling software. There were four districts identified
by Civitas, titled District 1, District 2, District 3, and District 4, respectively. District 4, a
single college district, was not considered a potential participant because it had
purchased, but not yet received any training required to implement, the Illume product.
The three California community college districts identified as potential participants were
District 1, located in southern California with three colleges within its system; District 2,
located in central California with two colleges within its system; and District 3, located in
northern California, with four colleges within its system. The annual headcount for the
colleges for within Districts 1 through 3 are provided in Table 5.

There were potentially nine administrators (Figure 4) with titles of CSSO at the
colleges listed in Table 5 if positions were not vacant or combined, and position-holders
are willing and able to participate with data collection. Each of these districts has
purchased and received training and/or implemented the Civitas Illume predictive-
modeling software. This software product combines disparate college and district data
from diverse institutional sources, e.g. student information and learning management
systems, to calculate student persistence models using data provided by each district.

Table 5.

*Selected California community colleges demographic information*

<table>
<thead>
<tr>
<th>District</th>
<th>Name</th>
<th>Location</th>
<th>2015-16 Annual Headcount</th>
</tr>
</thead>
<tbody>
<tr>
<td>District 1</td>
<td>College A</td>
<td>Southern California</td>
<td>17,529</td>
</tr>
<tr>
<td></td>
<td>College B</td>
<td>Southern California</td>
<td>17,050</td>
</tr>
<tr>
<td></td>
<td>College C</td>
<td>Southern California</td>
<td>28,880</td>
</tr>
<tr>
<td>District 2</td>
<td>College D</td>
<td>Central California</td>
<td>4,335</td>
</tr>
<tr>
<td></td>
<td>College E</td>
<td>Central California</td>
<td>5,917</td>
</tr>
<tr>
<td>District 3</td>
<td>College F</td>
<td>Northern California</td>
<td>45,558</td>
</tr>
<tr>
<td></td>
<td>College G</td>
<td>Northern California</td>
<td>19,866</td>
</tr>
<tr>
<td></td>
<td>College H</td>
<td>Northern California</td>
<td>12,032</td>
</tr>
<tr>
<td></td>
<td>College I</td>
<td>Northern California</td>
<td>32,516</td>
</tr>
</tbody>
</table>

*Note.* Reflects 2015-16 unduplicated annual student count from the California Community College Chancellor's Office Data Mart (http://datamart.cccco.edu/Students/Student_Term_Annual_Count.aspx)

**Sampling**

Purposeful sampling has been described as sampling that illuminates the subject
and offers a “useful manifestation of the phenomenon of interest; sampling, then, is
aimed at insight about the phenomenon, not empirical generalization from a sample to a
population” (Patton, 2015, Exhibit 2.1, p. 46). The nine college CSSOs who met the
criteria for participation were approached to determine their willingness to take part in
interviews. CSSO contact information was obtained by reviewing district and college
websites for email and telephone information.
Volunteer sponsors, other CSSOs, sent an introductory email identifying the researcher, informing potential participants of this study and asking them to consider participating in it. After this, the researcher emailed potential participants, explaining the purpose of the study and asking for them to volunteer to be part of the study. Follow-up emails or telephone calls were made to provide more information regarding the study or pursue confirmation of participation. Interview dates were made with five of the nine CSSOs who indicated a willingness and availability to participate. These five CSSOs represented two of the three districts identified in the target population of the study.

**Instrumentation**

Both qualitative and quantitative data were collected for use in this case study. Archival data were collected from the California Community College Chancellor’s Office (CCCCO) Management Information Systems (MIS) Data Mart. Qualitative data were in
the form of open-ended interviews and documents supporting the case-study methodology. Both sets of data were used to provide answers to the research questions.

Archival Data

The CCCCO MIS Data Mart unit is responsible for collecting data from 113 community colleges and 72 college districts in a general repository and releasing that data as needed to the public upon request. Student information by term is collected and analyzed by the MIS unit and used for general release to the legislature and citizens of California. The CCCCO allows release of these data for research studies. Academic year 2015-16 was the most current complete year of history in the Data Mart. “When a researcher analyzes data that have been collected by some other organization, group, or individual at some prior time, the work is called secondary data analysis” (McMillan & Schumacher, 2010, p. 242).

A comprehensive mandated schedule (Figure 5) of data collection occurs throughout the academic year within the Data Mart organization. Each college and district submits files laying out data elements for inclusion into the data repository at the state. The Data Mart falls under the management information systems (MIS) of the state chancellor’s office division of technology, research and information systems, which has responsibility for:

- Data collection
- Maintenance of the data element dictionary
- Data-reporting services for federal and state agencies
- Data warehousing and systems development
- Ad-hoc data querying services, and
• Decision support systems (CCCCO Management Information Systems website, 2016, p. 1).

Figure 5. Sample MIS data submission timeline - Retrieved from http://extranet.cccco.edu/Divisions/TechResearchInfoSys/MIS.aspx

Each unique data element provided by the colleges was checked for field, integrity, and quality by the CCCCO MIS. If any one element failed to pass the edits, the entire file was returned to the college or district for error corrections and resubmittals. This process continued until an error-free file was submitted.
Interviews and Documents

The interview questions were developed to allow participants to tell their stories and describe their experiences and perceptions. The literature review identified limited research addressing how administrators use predictive modeling to improve student course completion rates and supported the need to identify factors perceived as most relevant to administrators. The purpose statement and research questions, in combination with findings from the literature review synthesis matrix (Appendix A), were used as the initial guides to create semi-structured interview questions. Semi-structured questions allow the researcher to ask follow-up questions of the interviewee to provide clarification or additional information to the original response. After final edits to the interview questions (Appendix B) were made and alignment was ensured with the research questions (Appendix C), approval to proceed with data collection was requested and approved (Appendix D) by the Brandman University Institutional Review Board (IRB).

An initial email (Appendix E) was sent to the sample group at the three districts. This email included an introduction, the purpose of the study, and an invitation to participate in interviews. The informed consent document (Appendix F) was attached and referenced in the email. Respondents who indicated a willingness to participate were then contacted to schedule a date and time for the interview. An email was sent, verifying the scheduled interview with date, time, participant rights, assurance of anonymity, and ability to withdraw at any time. A courtesy reminder email was sent approximately three business days prior to the scheduled meeting, again reiterating participant rights. At the interview, the participants were again reminded of their rights, their anonymity, and their ability to stop the interview at any time. Additional
information was given that this was a semi-structured interview and would allow the researcher the flexibility to ask follow-up questions to clarify or provide more depth to answers. Documents and other artifacts such as meeting minutes, reports, or web sites referenced by the interviewees were noted and examined.

**Validity**

Validity in research has been defined as an indication of how well a test instrument measures what is meant to be measured (Creswell, 2013; Patton, 2015). The term “face validity” (Patton, 2015, p. 26) refers to whether the instrument will measure what is intended with assurance and credibility. “Qualitative analysis is driven by the capacity for astute pattern recognition from beginning to end (Patton, 2015, p. 653).”

Collection of information from the participants involved accurate transcription of interviews and all supplemental written information provided.

Archival data were requested and collected from the CCCC0 MIS Data Mart, a data repository of the public community college system. These data were thoroughly checked and cross-checked during the state-controlled submission and edit processes before acceptance into the repository. A common data element dictionary was used to ensure the values reported were representative of college and district records.

**Pilot test.** Interview questions were developed to answer the research questions and field-tested with non-participating administrators. A first draft of interview questions was given to two administrators not participating in the study. These non-participants were asked to review the interview questions for ease of understanding and context toward answering the research questions and providing suggestions for change to the researcher. After revisions were made, a mock interview was held with a third non-
participating administrator and an observer for timing and flow of questions. After this interview, the interviewee and observer were asked to comment on the interview and provide any suggestions for improvements or change. These comments and suggestions were incorporated into the final draft of interview questions (Appendix B).

**Reliability**

Reliability in a research study is often defined as the ability to repeat one’s findings in the absence of change (Creswell, 2014; McMillan & Schumacher, 2010; Patton, 2015). If this study were repeated, its reliability would be measured on its ability to yield similar results where conditions are unchanged. Reliability may be evaluated by reviewing how data were collected, entered and reviewed (Patton, 2015).

**Intercoder reliability.** Each participant was asked the same set of semi-structured interview questions. The transcribed interviews were imported into NVivo software for coding—a process that allows assignments of groupings or categories because of a common, shared characteristic (Saldana, 2009). Because these defined codes are subjective in nature, a second peer researcher coded 10% of the collected data. This secondary coding by an independent researcher ensured a minimum of 70% agreement in coding decisions with the primary researcher. One definition of intercoder reliability states it is the “extent to which two or more independent coders agree on the coding of the content of interest with an application of the same coding scheme” (SAGE Research Methods website, 2008, p. 1). The researcher provided a secondary, independent researcher with the interview transcripts, the purpose statement, and research questions. The secondary coder also used NVivo software to upload the transcripts and code the data. The results of the secondary coding were shared and compared to the
primary researcher’s coding outcomes. The researchers agreed on 70% agreement as a criterion for intercoder reliability. Percentage agreement between coders is one method of ensuring intercoder reliability.

The Data Mart data element dictionary describes each individual piece of data collected as well as processing edits. The first MIS edit would be a field check to determine if the appropriate, valid data were provided in the uploaded file from the college or district. If the field check passes, the next processing edit validates integrity, meaning the data provided is not inconsistent with other relational data associated with that field. After the integrity check, a quality check process determines if the field value makes sense—essentially asking whether the data is consistent with other related data provided and other associated requirements of the data. A sample (Figure 6) for data element SS02, Student-Credit-Course-of-Study, from the CCCC0 MIS Data Mart data element dictionary shows the relationship between the processing edits.

![SS02 Data Element Dictionary](http://extranet.cccco.edu/Divisions/TechResearchInfoSys/MIS.aspx)

Figure 6. Sample CCCC0 MIS Data Mart data elementary dictionary for field value SS02

Triangulation of data from multiple sources assists to strengthen and add depth so that the analysis and report is comprehensive and well-developed (Patton, 2015; Yin,
“The most robust evidence may be considered to have been established if the data from three independent sources all coincide” (Yin, 2012, Box 11). Coded themes from interview transcripts and archival data were used to triangulate the data. Using multiple data sources allows the researcher to gain confidence, sensitivity and closeness to the phenomenon being studied.

The reliability of this study was enhanced through: (a) ensuring sample population met selection criteria, (b) field testing of interview questions, (c) consistent data collection and analysis, and (d) in-depth documentation of the research process. The California Data Mart provided assurance of reliability based on their methods of collecting, editing, and validating the data.

**Data Collection**

Multiple types of data including interview transcripts, artifacts, and archival data were collected. After final edits to the interview questions were made (Appendix B), approval to proceed with data collection was requested and approved by the Brandman University Institutional Review Board (BUIRB) (Appendix D). The MIS Data Mart public site was accessed for release of non-identifiable student information related to successful course completions.

**Archival Data**

Archival data were retrieved from the California community college system data repository and reviewed to determine differences in successful course completions rates at the participating administrators’ colleges. Archival data are data already collected by another institution or organization (McMillan & Schumacher, 2010)—in this case, the California state Data Mart—for use of and analysis by the researcher. There were many
reasons to use archival data including efficiencies of time and costs, “data quality, [and] increased sample size” (McMillan & Schumacher, 2010, p. 242). With an increased sample size, subsets of data may be analyzed with “improved reliability, and generally credible results” (McMillan & Schumacher, 2010, p. 243). Specific data included course success rates that allowed analysis and comparison within the CCC system and between individual colleges.

Unduplicated student data were requested that include all of the data items needed to address the research questions related to course completions at the participating community college districts. The request made to the CCCCO MIS Data Mart allowed access to the successful course-completion data for extraction and review, leaving individual students anonymous. This allowed the researcher to determine the sample colleges’ current course completion rates in preparation for participant interviews. The data were populated in tables and accompanied by narrative describing the relationships found. Once processed, this data was further reviewed and compared to data acquired in the CSSO participant interviews.

**Interviews**

Potential interview participants were identified and initial contact was made directly to determine their willingness to participate in the research. In some instances, the researcher networked with personally known individuals within the California community college system, requesting introductions to potential participants. Most initial contacts were made via email. The email identified the researcher, described the purpose of the study, assured confidentiality of responses and asked for a response indicating willingness to participate along with their calendar schedulers contact information. For
those responding who indicated willingness to participate, the researcher contacted the person or scheduler and arranged a date and time not to exceed 60 minutes for a short in-person interview. For those administrators who, because of lack of in-person availability, were unable to meet in person, a Skype or telephone interview was proposed. The researcher confirmed all schedules via email and thanked the administrators for participating. A few days before the scheduled interview, the researcher sent another email re-confirming the date, time, and location of the interview. This email included a list of planned questions along with the possibility of follow-up questions depending on answers.

At the scheduled interview day and time, the researcher met with the participant and again reassured the administrator of confidentiality as well as the ability to append the transcribed record of the interview that was being recorded. The researcher used two recording devices to limit loss of data caused by technology issues. The interview commenced using the structured questions but allowing for follow-up questions for clarification or further information. Being respectful of the administrator’s time and other calendared meetings, the researcher vigilantly monitored time throughout the interview. The researcher thanked the participant at the end of the interview, reminded the participant that a transcription of the recorded interview would be available in a prescribed timeframe and that the participant could contact the researcher if they would like to add new or additional information or provide artifacts to support their responses.

The recorded interviews were transcribed by the researcher by listening to the recording multiple times. Through multiple reviews of the recording with the transcript, an accurate transcription was ensured. Once validated for accuracy, the transcriptions
were emailed to the administrator with a prescribed response date for edits, corrections, or enhancements. If the administrator responded within the time frame, any additions or edits were included as appended to the interview. If the administrator did not respond, the original transcription was used. The approved transcriptions were then used with NVivo software to identify themes and produce tables of data for review and analysis.

When study participants were asked open-ended, thoughtful questions during the interview, the answers reflected the individuals’ beliefs and experiences. By asking follow-up questions for clarification or understanding, a more thorough understanding of the individual experience unfolds (Patton, 2015). Consistent semi-structured conversations with open-ended questions allowed participants to expand their answers or tell their stories.

Participants were interviewed in person or, for those not available in person, through Skype or telephone. The researcher practiced, in advance of scheduled interviews, the interview process for both timing and sequencing of questions with volunteer non-participating administrators. Prior to the interview, the participants were forwarded the list of questions along with reminders that they would remain anonymous, have an opportunity to review and correct the transcript of the interview, and provide new information.

After the interview concluded and the participant had been thanked, the researcher reminded the participant that a transcript of the interview would be made available for review and corrections or to provide new information. Additionally, the participant was reminded that they may contact the researcher if they had any questions concerning the process or if they had supplemental information, artifacts, to provide to the researcher.
Documents

Artifact discovery was either performed directly by the researcher or provided by the participant. Various artifacts were explored to gather information and provide context to the administrator experience using predictive-modeling data to identify students at risk of not completing their courses. The artifacts included institutional reports and websites with information on course completion rates at California community colleges and districts. Additional artifacts in the form of meeting minutes, board reports and annual reports were presented and considered for inclusion dependent on ability to answer the research questions.

Data Analysis

Results were reviewed and analyzed for distinct sets of data. The first set included interview transcripts. The second set was archival data retrieved from the California community college system data repository, the CCCCO MIS Data Mart. Additionally, documents were reviewed and included if they addressed the research questions and purpose of the study. The data collected and analyzed attempt to describe and answer the how and why of administrators’ utilization of predictive modeling to increase successful course completions at their colleges. The case-study analysis “followed a pattern matching procedure” (Yin, 2012, p. 39) where the “role of theory was to specify the descriptive differences” (Yin, 2012, p. 39) and similarities between the colleges and their utilization of predictive modeling.

Archival Data

The CCCCO MIS Data Mart collects a cross-section of data representing all 72 college districts. These data include course success rates or, as stated for this study,
course completion rates that may be reviewed and compared over periods of time. These data were then disaggregated by college to report comparisons of course completion rates for the sample districts to answer RQ1. These data are provided in tables in Chapter IV.

**Interviews**

Patton (2015) suggests, “qualitative analysis aims to make sense of qualitative data: detecting patterns, identifying themes, answering the primary questions framing the study, and presenting substantively significant findings” (p. 658). Data from interviews were coded using NVivo software. NVivo allowed ease of identification and creation of themes that answered the research question. Instead of a manual tabulation of codes and themes, the software kept track of selected data with associated themes. Once emergent themes were identified, the researcher reduced these themes and synthesized them to determine “where the essence and lived experience of the participants were realized, without interpretation or influence by the researcher” (Parsons, 2012, p. 68). Reports were then generated out of NVivo, allowing the researcher quick access to a variety of quotes to associate with the narrative story of this qualitative study.

To reduce the potential of researcher bias, the researcher used the following protocols:

- a neutral location, typically the participant’s office, was used for all interviews. A quiet, serene, easily accessible room was used on campus;
- standardized semi-structured conversations with open-ended questions allowed participants to expand their answers or tell their stories;
- understanding that the researcher was the instrument, the researcher strove to limit or exclude interpretations to the data and take it as presented;
• the researcher allowed the participants to check the transcriptions against the
digital recordings for accuracy.

The findings were not presented to participants for verification purposes. Patton (2015)
suggests that an “ordinary person is unlikely to know” (p. 118) the processes used to
determine findings, and thus findings should not be presented to participants for
verification purposes. All data were organized in tables with descriptions and qualifiers
for presentation in Chapter IV.

Documents

Patton (2015) suggests that the review of artifacts, including existing documents
like meeting minutes and board reports, provides an additional context and perspective to
qualitative research. Artifacts can take different forms and provide traces of material to
add to interview transcripts. Revelations from these artifacts may include background
and history or goals and objectives to help answer, in part, the research question. NVivo
software was used to process and analyze the artifacts considered as answering the
research questions. Each set of data was organized in tables and presented in Chapter IV.

Limitations

By using California community college administrators’ experiences and words,
the participants provide their personal perspectives. Course success rates accessed from
the CCC Data Mart was used along with documents identified as answering the research
questions. Potential limitations of the study are:

1. sample size too small to relate findings to the larger population (McMillan &

Schumacher, 2010);
2. participants’ self-reported perceptions may be biased by other events or factors;
3. timing and availability constraints of the participants may limit participation;
4. predictive-modeling software models are unique to each college or district;
5. complexities of using historical data in a changing environment to predict future events or outcomes;
6. archival data analysis results rely on data accuracy as provided by individual CCCs and districts, consistency in interpretation of definitions and corresponding translations of data to meet the CCCCO MIS reporting standards, and application of standard reporting rules as regulated by the state chancellor’s office;
7. the number of California community colleges utilizing predictive-modeling software is not currently collected; and
8. while the researcher attempts to remain unbiased during the process, the researcher may unconsciously insert bias.

Summary

This chapter began with a restatement of the purpose of the study and the research questions. The chapter included a discussion of the methodology, research design, the proposed population and the target and sample populations. An in-depth description and review of the instrumentation, data collection and analysis, along with acknowledged limitations of the study, were included.
CHAPTER IV: RESEARCH, DATA COLLECTION, AND FINDINGS

This chapter presents the research, data collected, and findings from this case study. California Data Mart archival data and pertinent public documents were collected to address the purpose of the study. Five California community college (CCC) administrators in the role of chief student services officer (CSSO) were interviewed for their perceptions of those factors of predictive-modeling software having the most importance for improvement of successful course completion rates at CCCs for at-risk students.

**Overview**

Data for this case study included archival data from the California Data Mart and interviews with CCC administrators acting as CSSOs at colleges or districts where predictive-modeling software was purchased. Additional criteria for the CSSOs interviewed were either training received and/or exposure to the concepts of using predictive modeling at their campuses. By pursuing this research, a better understanding of data-driven decisions by CCC administrators to increase student course completions at California community colleges was explored. The results of this study may help create more comprehensive data-mining and analytic reports to support improved practices toward student retention and successful completion. This chapter includes a restatement of the purpose statement and research questions, a summary of the research methods and data-collection procedures, the population and sample with demographic data, presentation and analysis of the data, and summary.
Purpose Statement

The purpose of this case study was to determine the impact of utilizing predictive modeling to improve successful course completion rates for at-risk students at California community colleges. A secondary purpose of the study was to identify factors of predictive modeling having the most importance for improving successful course completion rates for at-risk students as perceived by California community college administrators.

Research Questions

RQ1: What was the impact of utilizing predictive modeling to improve successful course completion rates for at-risk students at California community colleges?

RQ2: What factors of predictive modeling have the most importance for improving successful course completion rates for at-risk students as perceived by California community college administrators?

Research Methods and Data-Collection Procedures

A case study was selected as the research method for this study. Quantitative data in the form of district and college documents and archival data from the California Data Mart were collected. Qualitative data and direct interviews with CSSO participants were collected to enhance the strengths of each type of data. Using multiple data sources with a case-study approach allowed for a greater understanding of the data and provided “cross-data validity checks” (Patton, 2015, p. 316). The researcher became familiar with retention and success rates at each college by first collecting archival data. These archival data provided perspective to the participant responses as collected via direct interviews.
Archival Data

Retention and success data were collected and placed in tables for each of the seven colleges where CSSOs participated in interviews for the fall and spring semesters starting with Fall 2013 through Fall 2016. Archival data were collected and reviewed because the dataset contained the variables needed to calculate reported course completions by colleges and included the sample population that met the criteria of the research questions. Additional considerations met were data accessibility, technical applications and assistance available.

Documents

Documents referenced by the interview participants or discovered by the researcher’s examination of accessible public records (BoardDocs, a software data repository used by some CCCs) were identified and reviewed. Those artifacts included minutes from board-of-trustees meetings and other like records. Only those documents that answered the research questions were considered for inclusion in this study.

Interviews

Research questions were developed and piloted with non-participating administrators. The questions were open-ended with the intent to explore the purpose of the study and answer the research questions. By using this qualitative method, the researcher added additional information that provides substance and humanity to the numbers. CSSO administrators were selected based on their district’s purchase of predictive-modeling software along with any training on or direct experience using predictive-modeling software. Interviews were recorded using a digital recorder and transcribed for ease of coding into NVivo software. NVivo software was used to identify
and code themes related to the qualitative data collected. An independent researcher volunteered to independently code transcribed interviews to determine reliability of themes identified by this study’s researcher. A rate of 70% or greater was required to assure intercoder reliability.

**Population**

McMillan and Schumacher (2010) describe a target population as “the total group to which results can be generalized” (p. 129). Within the 113 California community colleges, there are 2,153 (Figure 3) employees categorized as administrators (CCCCO, 2016). The target population identified for this study was 113 California community college administrators holding the position of chief student services officer (CSSO). CSSOs preside over student services departments and areas that are often non-instructional in nature but are tasked with outcomes associated with student success, in particular those services that assist students with persistence and course completions.

**Sample**

Each college of the 113 California community college system has a position identified as the CSSO. For the sample population, Civitas Learning Inc., one vendor of predictive-modeling software, provided names of districts that had purchased their product. Of the four districts identified by Civitas, three districts had administrative CSSOs who received sufficient training with and/or exposure to the software to qualify for the study. Within those three districts, one district in southern California had three colleges; one district in central California had two colleges; and one district in northern California had four colleges. A combined total of nine CSSOs were identified as potential participants in the sample population. The nine CSSOs were contacted and
asked to participate. Each was given a summary of the research study, a copy of the informed consent, and a participant’s bill of rights. However, due to competing priorities and availability, only five of the nine CSSOs agreed to participate in the research. These five CSSOs were from Districts 1 and 2 and represent the sample population.

**Demographic Data**

Preliminary information collected from participants during the interviews included demographic information (Table 6), including the numbers of years holding the position of CSSO at their college, the name of the predictive-modeling software, and the approximate date the software was implemented in a production environment for general use at the college.

**Table 6**

*Participants’ demographic information—self-reported within interviews*

<table>
<thead>
<tr>
<th>District</th>
<th>College</th>
<th>Years as CSSO</th>
<th>Gender</th>
<th>Predictive-Modeling Software</th>
<th>First use of predictive-modeling software in a production environment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A</td>
<td>2.5</td>
<td>Male</td>
<td>Civitas Illume</td>
<td>June 2016</td>
</tr>
<tr>
<td>1</td>
<td>B</td>
<td>0.6</td>
<td>Female</td>
<td>Civitas Illume</td>
<td>June 2014</td>
</tr>
<tr>
<td>1</td>
<td>C</td>
<td>1.0</td>
<td>Male</td>
<td>(1)</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>D</td>
<td>3.5</td>
<td>Female</td>
<td>Civitas Illume</td>
<td>June 2016 (2)</td>
</tr>
<tr>
<td>2</td>
<td>E</td>
<td>8.0</td>
<td>Female</td>
<td>Civitas Illume</td>
<td>June 2016</td>
</tr>
</tbody>
</table>

(1) A final determination of the use of Civitas Illume has not yet been made.
(2) Respondent uncertain whether general use was broadly available.

The researcher did not exempt the interviews for the CSSOs who indicated either current non-use of Civitas predictive-modeling software or no knowledge of the Civitas software used in a production environment. Both participants were able to answer, in detail, to the use of predictive analytics and modeling software and related to the Civitas software specifically, or in general, those interview questions that were specific to the
research questions. Therefore, these two interviewees were included as viable participants for this case study as they met the research criteria: they both had exposure through training and awareness of the potential uses for the Civitas Illume predictive-modeling software.

**Presentation and Analysis of Data**

Only the data addressing the purpose statement and answering the research questions are presented and analyzed. Because the study assured anonymity of the participants, the name of the participant, the college, or district is not identified. Any identifying information from interview transcripts, archival data or artifacts was redacted.

**Research Question 1**

In combination with archival data and artifact review, five CSSOs were interviewed and asked a series of semi-structured questions to address the first research question: What was the impact of utilizing predictive modeling to improve successful course completion rates for at-risk students at California community colleges? To describe the impact, the researcher first looked at pre-established course completion and success rates as calculated by the California Data Mart (Data Mart) for all California community colleges. The system-wide cumulative rates were then compared to the participating sample colleges’ success rates. These data provide a review of the past seven primary semesters, Fall 2013 through Fall 2016 respectively, for the CCC system and each of the five sampled colleges. Winter and Summer sessions were not included as these were considered optional terms of attendance for students. Fall 2016 was the last available full term as reported to the Data Mart by the colleges. Because this research explores those course successes leading to a degree, certificate or transfer, only credit
courses that were degree-applicable or transferrable were included in the data extracted. Basic skills (remedial or pre-college level) and non-credit course enrollments were not retrieved or reviewed.

The CCC calculated system-wide retention and success rates along with enrollment, retention and success counts are provided in Table 7. As presented in Table 7, the cumulative course enrollment counts from Fall 2013 to Fall 2016 decreased by 4.51%. The retention rate across the terms ranged from a low of 85.62% to a high of 86.50%. When comparing Fall 2013 to Fall 2016, the success rate increased by 0.95% from 69.48% to 70.43%, respectively.

Table 7

*Cumulative California Community Colleges retention and success rates Fall 2013 – Fall 2016*

<table>
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<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>RETENTION COUNT (2)</td>
<td>3,936,347</td>
<td>3,837,865</td>
<td>3,915,830</td>
<td>3,787,371</td>
<td>3,908,196</td>
<td>3,750,960</td>
<td>3,758,840</td>
</tr>
<tr>
<td>RETENTION RATE</td>
<td>86.27%</td>
<td>85.85%</td>
<td>86.02%</td>
<td>85.63%</td>
<td>86.15%</td>
<td>86.01%</td>
<td>86.50%</td>
</tr>
<tr>
<td>SUCCESS COUNT (3)</td>
<td>2,734,992</td>
<td>2,669,979</td>
<td>2,709,263</td>
<td>2,639,854</td>
<td>2,724,223</td>
<td>2,648,708</td>
<td>2,647,399</td>
</tr>
<tr>
<td>SUCCESS RATE</td>
<td>69.48%</td>
<td>69.57%</td>
<td>69.19%</td>
<td>69.70%</td>
<td>69.71%</td>
<td>70.61%</td>
<td>70.43%</td>
</tr>
</tbody>
</table>

Notes:
(1) Enrollment count is number of enrollments with grade of A, B, C, D, F, P, NP, I, IPP, INP, FW, W, DR
(2) Retention count is number of enrollments with grade of A, B, C, D, F, P, NP, I, IPP, INP, FW
(3) Success count is number of enrollments with grade of A, B, C, P, IA, IB, IC, IPP

The data retrieved from the Data Mart (Tables 8 – 12) provide retention and success rates for the five colleges associated with the participants who were interviewed. Total enrollment, retention, and success counts for fall and summer terms were extracted and included in Tables 7 – 12 as the basis for calculating retention and success rates.
**District 1 – southern California.** District 1 includes three community colleges—Colleges A, B, and C. As extracted from the Data Mart, data in Tables 8-10 reflect the individual retention and success rates of the individual colleges dating back to Fall 2013. These tables provide term-specific data as reported by the colleges from Fall 2013 through the last available full term reported, Fall 2016, to the Data Mart.

At the July 16, 2014 Board of Trustees meeting, as reflected in the minutes, the board “approved two contracts between Civitas Learning, Inc., and [District 1 – College A and College B], respectively. The contracts are for implementing Civitas Learning web-based applications aimed at improving student success.” The goal or purpose of the purchased software was presented by district staff as:

The Civitas services, application, and support will provide the Colleges with an innovative tool that uses data analytics to help us identify students who are at risk of failing in courses and programs. The platform will allow the Colleges to deliver personalized recommendations directly to students, faculty, advisors and administrators through intuitive, easy-to-use, Web-based applications to enable better-informed decisions that lead to improved student success. We are confident that [the district Colleges] will benefit from the services and retain many more than the 25 FTES (Full Time Equivalent Students) worth of students that we lose between the first day of class and the census date, which would more than cover the cost of the Civitas product and services (District 1 Board Minutes, Item 11, July 16, 2014).

**College A.** As an informational item, College A presented to its district Board of Trustees at the October 20, 2015 meeting, their 2015-16 Student Success and Support
Program (SSSP) annual report, which included the statement: “The College is currently working with Civitas to develop analytics to build a robust early alert system” (p. 26).

The report continues to state:

This system allows the College to engage data for effective decision-making regarding student success. It allows the tracking of student performance by course, assignment and behavior to provide a clearer image of the student’s performance as well as the College’s performance. Civitas is more than an early alert system for student performance. It is a platform to analyze institutional behavior for effective decisions based on data. (SSSP, 2015-16, p. 27)

Additionally, the report lists Civitas as a technology tool used specifically by student support services.

For College A, Table 8 provides Data Mart extracted counts and success rates specific to their college. Table 8 notes that Fall 2016 is the first term associated with use of predictive-modeling software.

Table 8

*College A retention and success rates Fall 2013 – Fall 2016*

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>ENROLLMENT COUNT (1)</td>
<td>20,977</td>
<td>22,791</td>
<td>22,751</td>
<td>24,125</td>
<td>23,138</td>
<td>24,324</td>
<td>21,413</td>
</tr>
<tr>
<td>RETENTION COUNT (2)</td>
<td>17,350</td>
<td>18,283</td>
<td>18,504</td>
<td>19,687</td>
<td>18,810</td>
<td>20,299</td>
<td>17,968</td>
</tr>
<tr>
<td>RETENTION RATE</td>
<td>82.71%</td>
<td>80.22%</td>
<td>81.33%</td>
<td>81.60%</td>
<td>81.29%</td>
<td>83.45%</td>
<td>83.91%</td>
</tr>
<tr>
<td>SUCCESS COUNT (3)</td>
<td>13,480</td>
<td>13,760</td>
<td>14,552</td>
<td>15,658</td>
<td>14,950</td>
<td>15,947</td>
<td>14,128</td>
</tr>
<tr>
<td>SUCCESS RATE</td>
<td>64.26%</td>
<td>60.37%</td>
<td>63.96%</td>
<td>64.90%</td>
<td>64.61%</td>
<td>65.56%</td>
<td>65.98%</td>
</tr>
</tbody>
</table>

Notes: Highlighted term represents first term Civitas Illume predictive modeling used as reported by CSSO
(1) Enrollment count is number of enrollments with grade of A, B, C, D, F, P, NP, I, IPP, INP, FW, W, DR
(2) Retention count is number of enrollments with grade of A, B, C, D, F, P, NP, I, IPP, INP, FW
(3) Success count is number of enrollments with grade of A, B, C, P, IA, IB, IC, IPP
While enrollment increased by a few hundred students, the retention rates for Fall 2016 show a 1.20% increase over Fall 2013. The success rate, when comparing these same terms, increased by 1.72%.

**College B.** As reported to its district Board of Trustees at their October 2014 meeting, College B noted in its 2014-15 SSSP plan for credit students:

Improving student success is one of our six master planning goals. In addition, student success and completion are significant benchmarks for our College. While we have made progress in improving student success, we still need better tools to help continue to improve student success. Civitas services, application, and support will provide the College with an innovative tool that uses data analytics to help us identify students who are at risk of failing in courses and programs. The platform will allow the College to deliver personalized recommendations directly to students, faculty, advisors and administrators through intuitive, easy-to-use, Web-based applications to enable better-informed decisions that lead to improved student success. We are confident that [College B] will benefit from the services and retain many more students than we lose between the first day of class and the census date. (SSSP, 2014-15, p. 20)

For College B’s 2015-16 SSSP annual report to the CCCCO, an additional statement was added:

The Inspire for Advisor module serviced by Civitas will be introduced in the Fall 2015 semester. The module gives the risk of students not persisting by placing them in one of five categories. This data will allow counselors to intervene and give targeted messages before they drop courses (SSSP, 2015-16, p. 38).
Both the district and college reference Civitas products as a tool to improve student success.

The data provided in Table 9 indicates College B has seen a 10.82% decrease in course enrollments from Fall 2013 to Fall 2016. First-term usage of predictive modeling software is noted as Fall 2014. Retention rates improved by 0.52% during this same period. College B success rates showed the most improvement, compared to the other colleges in this study, with an increase of 2.25%.

Table 9

College B retention and success rates Fall 2013 – Fall 2016

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>ENROLLMENT COUNT (1)</td>
<td>34,685</td>
<td>34,471</td>
<td>33,862</td>
<td>33,817</td>
<td>32,208</td>
<td>33,027</td>
<td>30,932</td>
</tr>
<tr>
<td>RETENTION COUNT (2)</td>
<td>29,863</td>
<td>29,192</td>
<td>29,164</td>
<td>28,806</td>
<td>27,808</td>
<td>28,029</td>
<td>26,793</td>
</tr>
<tr>
<td>RETENTION RATE</td>
<td>86.10%</td>
<td>84.69%</td>
<td>86.13%</td>
<td>85.18%</td>
<td>86.34%</td>
<td>84.87%</td>
<td>86.62%</td>
</tr>
<tr>
<td>SUCCESS COUNT (3)</td>
<td>23,351</td>
<td>23,516</td>
<td>22,769</td>
<td>22,892</td>
<td>21,806</td>
<td>22,837</td>
<td>21,520</td>
</tr>
<tr>
<td>SUCCESS RATE</td>
<td>67.32%</td>
<td>68.22%</td>
<td>67.24%</td>
<td>67.69%</td>
<td>67.70%</td>
<td>69.15%</td>
<td>69.57%</td>
</tr>
</tbody>
</table>

Notes: Highlighted term represents first term Civitas Illume predictive modeling used as reported by CSSO (1) Enrollment count is number of enrollments with grade of A, B, C, D, F, P, NP, I, IPP, INP, FW, W, DR (2) Retention count is number of enrollments with grade of A, B, C, D, F, P, NP, I, IPP, INP, FW (3) Success count is number of enrollments with grade of A, B, C, P, IA, IB, IC, IPP

College C. The 2014-15 SSSP plan for College C was presented to the BOT in October 2015. The plan did not include any mention of Civitas Learning, data analytics, or predictive modeling. However, within College C’s SSSP plan, a section was included on follow-up for at-risk students that identified the targeted audience as those students who were enrolled in basic skills courses, were undecided about their course of study, or were on academic or progress probation or facing dismissal. The report did indicate that
students considered at risk of not completing were identified by individual faculty and counselors into a separate software system. In their updated 2015-16 plan, no mention is made of predictive modeling, data analytics, or the Civitas Learning software products.

An overview of the counts of students enrolled in courses from Fall 2013 through Fall 2016, the course retention counts, the course success counts, and the corresponding success rates based on these counts (Table 10) were extracted from the Data Mart.

Table 10

College C retention and success rates Fall 2013 – Fall 2016

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>ENROLLMENT COUNT (1)</td>
<td>66,498</td>
<td>66,406</td>
<td>66,078</td>
<td>66,349</td>
<td>66,659</td>
<td>65,191</td>
<td>65,210</td>
</tr>
<tr>
<td>RETENTION COUNT (2)</td>
<td>57,618</td>
<td>57,041</td>
<td>57,021</td>
<td>57,425</td>
<td>57,789</td>
<td>55,921</td>
<td>56,941</td>
</tr>
<tr>
<td>RETENTION RATE</td>
<td>86.65%</td>
<td>85.90%</td>
<td>86.29%</td>
<td>86.55%</td>
<td>86.69%</td>
<td>85.78%</td>
<td>87.32%</td>
</tr>
<tr>
<td>SUCCESS COUNT (3)</td>
<td>47,983</td>
<td>47,625</td>
<td>47,209</td>
<td>47,986</td>
<td>47,512</td>
<td>47,694</td>
<td>47,431</td>
</tr>
<tr>
<td>SUCCESS RATE</td>
<td>72.16%</td>
<td>71.72%</td>
<td>71.44%</td>
<td>72.32%</td>
<td>71.28%</td>
<td>73.16%</td>
<td>72.74%</td>
</tr>
</tbody>
</table>

Notes: Civitas Illume predictive modeling reviewed and considered but not yet in production per CSSO
(1) Enrollment count is number of enrollments with grade of A, B, C, D, F, P, NP, I, IPP, INP, FW, W, DR
(2) Retention count is number of enrollments with grade of A, B, C, D, F, P, NP, I, IPP, INP, FW
(3) Success count is number of enrollments with grade of A, B, C, P, IA, IB, IC, IPP

College C data reflects a 1.94% decrease in course enrollments from Fall 2013 to Fall 2016. Retention rates averaged 86.45% for the seven terms listed. When comparing Fall 2013 to Fall 2016, success rates improved by 0.58%.

District 2 – central California. District 2 purchased Civitas Illume and Inspire for Advisors and formalized the contract between the district and its colleges with Civitas on November 17, 2015 at a regular board meeting. At the December 8, 2015 board meeting, the trustees were presented, as part of a technology project summary report, this statement: “Civitas helps institutions build a scalable, sustainable and strategic analytics
infrastructure that unlocks disparate data sources that bring real-time insights to administrators, faculty, advisors, and students.”

**College D.** In the college’s final December 2015 equity report, the college identified activities to help students succeed. These activities included an early alert identification of at-risk students for intervention services; work with students on their educational plans to increase course and degree completion efforts; increase the number of students accessing tutoring and supplemental instruction; and encourage student enrollment in college success and life skills courses. Each activity, coordinated with support services, as presented in the report was tied to successful student course completions and completion of an educational goal.

Data Mart accessed data is reflected in Table 11 for College D. Enrollment, retention and success counts are reported by the college each term. From this data, retention and success rates are calculated by the CCCCO Data Mart system. The first term of use of predictive modeling was Fall 2016.

Table 11

**College D retention and success rates Fall 2013 – Fall 2016**

<table>
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</tr>
</thead>
<tbody>
<tr>
<td>ENROLLMENT COUNT (1)</td>
<td>7,501</td>
<td>6,919</td>
<td>7,354</td>
<td>7,039</td>
<td>7,126</td>
<td>7,685</td>
<td>8,776</td>
</tr>
<tr>
<td>RETENTION COUNT (2)</td>
<td>6,232</td>
<td>5,979</td>
<td>6,282</td>
<td>5,876</td>
<td>5,897</td>
<td>6,414</td>
<td>7,371</td>
</tr>
<tr>
<td>RETENTION RATE</td>
<td>83.08%</td>
<td>86.41%</td>
<td>85.42%</td>
<td>83.48%</td>
<td>82.75%</td>
<td>83.46%</td>
<td>83.99%</td>
</tr>
<tr>
<td>SUCCESS COUNT (3)</td>
<td>5,011</td>
<td>4,928</td>
<td>5,239</td>
<td>4,774</td>
<td>4,745</td>
<td>5,325</td>
<td>5,746</td>
</tr>
<tr>
<td>SUCCESS RATE</td>
<td>66.80%</td>
<td>71.22%</td>
<td>71.24%</td>
<td>67.82%</td>
<td>66.59%</td>
<td>69.29%</td>
<td>65.47%</td>
</tr>
</tbody>
</table>

Notes: CSSO unsure of broad-based use of Civitas Illume predictive modeling in production
(1) Enrollment count is number of enrollments with grade of A, B, C, D, F, P, NP, I, IPP, INP, FW, W, DR
(2) Retention count is number of enrollments with grade of A, B, C, D, F, P, NP, I, IPP, INP, FW
(3) Success count is number of enrollments with grade of A, B, C, P, IA, IB, IC, IPP
College D is showing a slight downward trend from its high 71.24% in Fall 2014 to a rate of 65.47% in Fall 2016, reflecting a success rate loss of 1.33% from Fall 2013.

**College E.** At the January 29 and 30, 2016 Board of Trustees retreat, a presentation was made showing a diagram that details “how multiple programs and data sources can feed into their [Civitas] products and provide us [Colleges] with data and analysis that will strengthen student success efforts.” Additionally, a report by staff to the board at this same meeting indicated that student success is data-driven with actions and outcomes leading to degree completion and career success.

As presented in Table 12, Data Mart reported enrollment, retention, and success counts are shown for the seven terms starting in Fall 2013 and ending Fall 2016. The calculated success rate showed College E with the largest increase, 3.30%, in success when compared to Fall 2013. Fall 2016 is noted as the first year of using predictive modeling. This increase is the largest rate increase of the five colleges reported in this sample and exceeds the Fall 2016 system-wide rate by 2.81%.

Table 12

*College E retention and success rates Fall 2013 – Fall 2016*

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
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<tbody>
<tr>
<td>ENROLLMENT COUNT (1)</td>
<td>11,259</td>
<td>11,369</td>
<td>11,209</td>
<td>11,023</td>
<td>10,852</td>
<td>10,982</td>
<td>11,544</td>
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<td>RETENTION COUNT (2)</td>
<td>9,609</td>
<td>9,678</td>
<td>9,643</td>
<td>9,445</td>
<td>9,269</td>
<td>9,141</td>
<td>9,978</td>
</tr>
<tr>
<td>RETENTION RATE</td>
<td>85.35%</td>
<td>85.13%</td>
<td>86.03%</td>
<td>85.68%</td>
<td>85.41%</td>
<td>83.24%</td>
<td>86.43%</td>
</tr>
<tr>
<td>SUCCESS COUNT (3)</td>
<td>7,875</td>
<td>8,026</td>
<td>8,091</td>
<td>8,095</td>
<td>7,877</td>
<td>7,715</td>
<td>8,455</td>
</tr>
<tr>
<td>SUCCESS RATE</td>
<td>69.94%</td>
<td>70.60%</td>
<td>72.18%</td>
<td>73.44%</td>
<td>72.59%</td>
<td>70.25%</td>
<td>73.24%</td>
</tr>
</tbody>
</table>

Notes: Highlighted term represents first term Civitas Illume predictive modeling used as reported by CSSO
(1) Enrollment count is number of enrollments with grade of A, B, C, D, F, P, NP, I, IPP, INP, FW, W, DR
(2) Retention count is number of enrollments with grade of A, B, C, D, F, P, NP, I, IPP, INP, FW
(3) Success count is number of enrollments with grade of A, B, C, P, IA, IB, IC, IPP

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**Successful course completion rates.** The five participating colleges’ success-rate data were charted alongside the system-wide 113-college success rate (Figure 7). As noted in Figure 7, two of the colleges had success rates higher than the cumulative system-wide rate and were identified as College C (not yet using Civitas Illume) in Southern California and College E in Central California.

Both Colleges C and E were consistently higher than the system-wide success rate across the terms, except when College E dipped slightly below the system-wide average in Spring 2016 by 0.36%.

![Success Rates - Fall 2013 through Fall 2016](image)

*Figure 7.* Successful course completion rate comparison: CCC system-wide and sampled colleges by term.
However, when comparing the success rates obtained in Fall 2013 to those from Fall 2016 (Figure 8), the delta results indicate that three of the colleges, Colleges A, B, and E, surpassed the state rate. These three colleges exceeded the system-wide rate by a range of 0.77% to 2.35%. Only College D’s success rate declined when comparing those terms.

Figure 8. Success-rate percentage changes by sample colleges and system-wide Fall 2013 compared to Fall 2016

Because the study assured anonymity of the participants, the name of the participant, the college, and district were not identified. Instead participants were identified (Table 13) and referenced as Participant A, associated with College A, Participant B, associated with College B, etc.
Table 13

Participants’ Assigned Identification Legend

<table>
<thead>
<tr>
<th>Participant ID</th>
<th>College Association</th>
<th>District Association</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participant A</td>
<td>College A</td>
<td>1</td>
</tr>
<tr>
<td>Participant B</td>
<td>College B</td>
<td>1</td>
</tr>
<tr>
<td>Participant C</td>
<td>College C</td>
<td>1</td>
</tr>
<tr>
<td>Participant D</td>
<td>College D</td>
<td>2</td>
</tr>
<tr>
<td>Participant E</td>
<td>College E</td>
<td>2</td>
</tr>
</tbody>
</table>

Five CSSOs were interviewed and asked to describe the impact of using predictive-modeling software on improving successful course completion rates. The responses were synthesized and analyzed in narrative format and organized by emergent themes. After an initial review of the transcripts for coding, an additional review of the material refined the codes and frequency of references. Most of these themes as expressed by the participants emphasized outcomes anticipated or realized by the use of predictive modeling. The frequency of references is coded to these themes and found in Table 14.

Table 14

Codes and frequencies of themes found for research question 1 (RQ1)

<table>
<thead>
<tr>
<th>CODE</th>
<th>NUMBER OF PARTICIPANTS</th>
<th>FREQUENCY OF REFERENCES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increased student contact</td>
<td>5</td>
<td>21</td>
</tr>
<tr>
<td>Timely intervention strategies</td>
<td>5</td>
<td>18</td>
</tr>
<tr>
<td>Identify and monitor students</td>
<td>5</td>
<td>16</td>
</tr>
<tr>
<td>Sufficient support services</td>
<td>5</td>
<td>12</td>
</tr>
<tr>
<td>Successful completions and retentions to achieve educational goal</td>
<td>4</td>
<td>9</td>
</tr>
<tr>
<td>Institutional metrics and reporting</td>
<td>2</td>
<td>7</td>
</tr>
</tbody>
</table>
**Increased student contact.** This theme resonated throughout the interviews with the five participants. Participant E referred to this as “touch points.” Participant D stated:

I’m hoping the student uses it [predictive modeling] as much as the counselors can use it with them and for them to help them realize, on the fly, this is where you’re at, this is where you’re currently at, instead of them having to guess where they’re at.

The participant from College D indicated there was a need to let students know “that we’re really concerned about their overall well-being and not just, you know, are you going to be successful in this particular class.” On review of artifacts, reports for both the Student Success and Support Program (SSSP) and Student Equity (SE) plan emphasized increasing student contacts to provide a sense of belonging. Participants A and B noted something called the “nudge factor”, referring “to reminders and small pushes” to make students more aware of student support services and “nudge them and prod them in a better way.” Both SSSP and SE reports indicated a need for students to take responsibility and be aware of their responsibilities, like class attendance and completion of homework assignments, supporting their educational goals. However, Participant B said reaching out meant “we don’t want to inundate them with too many people, you know, bombarding them with the same information.” Instead, a softer intrusion of services was recommended by Participant B. Predictive modeling was “more of a unique connection to each individual student’s needs” according to Participant C. Participant D indicated that a student’s awareness of support services was “not the magic bullet but part of one that’s going to help.”
**Timely intervention strategies.** Related to student engagement and awareness, a common theme of “timely interventions” was mentioned by all of the participants. Participant B said “predicting their success early enough so that we can intervene, provide support, reach out to students” was an impact that the college was working toward with the use of predictive modeling. Timely interventions allowed the college to “customize” the strategy and provide a dedicated staff member reaching out to these students via email, via phone calls, to see if we can, you know, get them to come in, utilize our student support services and assist them with any kind of questions or concerns they may have.

Participant E indicated the impact would be “using the data to identify what the interventions to be or can be” and “knowing more precisely when to have that touch point.” College A stated that these interventions should not only be timely but also provide a “comprehensive response [that] consists of student services and academic affairs working together as a holistic response to at-risk students.”

**Identify and monitor students.** This was a common theme with all five interviewees. Participant A, referencing the Civitas software, stated it “only works as a compass to find at-risk students.” He went on to say that “once these at-risk students are identified, services and support can be setup for these students before they take a step into their first class.” Participant D said the software may be used “as a tracking system to follow students who don’t normally come through our doors.” However, Participant D also stated a hope that predictive modeling would only be used for positive things and provided this example:
From the demonstrations and the information we’ve gotten from the company, and shown what it’s going to look like, I would hope that it is something that is easy to use, that it isn’t used to profile students in a negative way, like, your chances of success in this course are less than 10%, you know…How are we as a group going to bring that information back to a student without totally, you know, putting up a wet blanket on their academic career here? I mean we need to get some things in place too. But I’m hoping we can use it for all positive things.

Participant D continued, stating that knowing as much as possible about individual students and their current behaviors is necessary in order to use predictive modeling:

As it has been presented … you see a student who, with the same characteristics, may not be successful but if you change this piece of it, the same students are doing really well. So, it can be something that can be used, I think very effectively with a student engagement piece if we call it, you know, a case management or however we get the students in to help use the software with them and not alone, saying they’re not going to make it—why bother with them?

For Participant D, additional information sources may provide more accurate indicators of future success.

If you use their GPA, what the classes they did in high school, don’t know anything about their study habits, or how much time they have to spend towards college, or do they even know they have to spend two hours for every one hour of class time, things like that. If you have those parameters for students and not just: You’re a 2.4 in high school and you didn’t do college prep, and you got a D in algebra, you’re not really going to do well in math here.
However, for Participant B, predictive modeling allowed the college to target those students who “are most at risk or moderately at risk for not persisting” and felt that with “the limited resources we have, we are able to target which group we will have the most impact on persistence.” She continued with this example:

If we have a very small group that’s at high risk, you know, we might want to not engage with that group as much as we would with the moderate at-risk group, which is a much larger number so we could have a more significant impact on them.

**Sufficient support services.** Participant A also referenced using predictive modeling to “target where to use its [College A’s] limited resources to support student retention.” These services, according to Participant B, provide “all the necessary support they [students] need to feel like they can continue and complete successfully.” Participant C pointed out that “it’s not the software but it’s the appropriate follow-through or assessment of the student by the institution” to provide the necessary support services. For College E, it was the “kinds of activities or resources or touch points we can put at certain places as success team initiatives.” All interviewees mentioned that creating and using sufficient types of support services was critical to a student’s completion of courses leading to their ultimate educational goal.

**Successful completions and retentions to achieve educational goal.** Four of the participants indicated completion and retention were outcomes needed to achieve a student’s education goal. For College A’s CSSO, “helping students meet their educational goals” and “increased student retention” were important outcomes to achieve from using predictive modeling. However, the CSSO at College C stated: “Sometimes, I am leery of, not fully convinced, that predictive analytics could, you know, holistically,
help all students.” He went on to say that he felt confident it would identify students that may need help but that it was up to the college to provide services that lead to retention and completion.

**Institutional metrics and reporting.** Only two of the interviewees indicated outcomes that related to reporting needs to external or internal sources. Participant A stated that predictive-modeling data was “a source of measurements/metrics for college MIS reporting, accreditation, grants, and our local success metrics.” For College C’s CSSO, data from the software may provide “accountability” information. Participant C stated: “We have the state’s terminology and the institutional terminology of student success, which is the overall objective, degree objective or transfer or certificate.” For College C, metrics looked at were “overall completion rates and each course completion overall translates to the overall objective of completion of degrees and certificates. Participant C went on to state: “It is really important for the college to show the data that, you know, how we are utilizing resources, and the overall success of our students.”

**Research Question 2**

The second research question asks, “What factors of predictive modeling have the most importance for improving successful course completion rates for at-risk students as perceived by California community college administrators?” This section of the chapter presents, as themes, the participants’ responses to interview questions that answered RQ2. Using the NVivo software, each transcript was reviewed by the researcher to locate and code themes that answered RQ2. After an initial review of the transcripts for coding, an additional review of the material refined the codes and frequency of references. These themes emphasized those factors considered important by the interviewees to address the
research question. As presented in Table 15, the codes used, number of participants responding with that theme, and the frequency of references were tabulated.

Table 15

*Codes and frequencies of themes found for research question 2 (RQ2)*

<table>
<thead>
<tr>
<th>CODES</th>
<th>NUMBER OF PARTICIPANTS</th>
<th>FREQUENCY OF REFERENCES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Planning and strategy</td>
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<td>41</td>
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<tr>
<td>Communication and training</td>
<td>4</td>
<td>25</td>
</tr>
<tr>
<td>Resources</td>
<td>4</td>
<td>24</td>
</tr>
<tr>
<td>Outcomes</td>
<td>5</td>
<td>21</td>
</tr>
<tr>
<td>Inclusion</td>
<td>5</td>
<td>18</td>
</tr>
</tbody>
</table>

**Planning and strategy.** Based on the interview responses, all five participants agreed that the most important factor, as determined by frequency of responses, was the planning and strategy before and during implementation of predictive modeling software. Participant A commented: “Plan, talk, plan, talk, and plan some more.” Participant B felt the planning should include “seeing what data we need, what data do we have, and is it accurate enough for the predictive analytics to be, you know, accurate, basically.” Participant C stated that a “post-implementation plan” was needed to “continuously improve it [predictive modeling].” From Participant D’s perspective, there is a need to ensure the data are “scrubbed enough that we can have a good dataset to work with and move forward with we think it’s going to show us as a predictor.” Many of the interviewees cited the need to collect specific data requirements, e.g., meeting attendance, progress within term, homework completions, quizzes and grades associated with them. Participant D stated: “It’s hard to engage students when you don’t know where they’re
at.” She continued by saying that she hoped for positive use of predictive modeling and that negatives could turn to positives:

Right now, everybody’s a 4.0 when they start, but this will tell you that they aren’t all 4.0…they have this in high school; they did this in high school; they didn’t do this in high school. You will know that they don’t all get a clean slate. They start off behind.

However, she continued by stating:

You might have a little bit better idea and the student might if they had some of the process of answering the questions that are more of a personal nature than just raw data that says this. I mean, anytime you can ask the student: how do you feel about college; what are your parents…are they supportive of you being here; do you have to work; the more that you can get those outside influences that affect success rates, the better off you’re going to be, coming from a student perspective and not just thinking or assuming that the student’s, you know, not going to do well because they were poor high-school students and they didn’t spend time. They could have been just really a hard worker that just didn’t get it.

For Participant E, it was a matter of “using the data to identify what the interventions need to be or can be.” Specifically, Participant E stated a need to “identify what problems are we trying to solve—we actually identify what the problem actually is. What does the data tell us? And then where do we need to go next with what kind of interventions?” Dr. Paul Dosal, the Vice President of Student Affairs and Student Success at University of South Florida and a Civitas Illume user, gave this advice when starting a predictive-modeling implementation:
Think carefully about how to best use the power that you now have a few clicks away. We didn’t think enough about that because we didn’t know exactly how transformative this would be for us. It took us some time to figure out the right structure and practice to fully use the data we have (Civitas Learning Inc. [Civitas], 2017, p. 7).

**Communication and training.** Four participants out of five indicated that communication and training were important factors of using predictive modeling to improve successful course completion rates. Communication was cited as part of an inclusive environment to ensure faculty and staff were aware of and participated in the implementation needs required of predictive modeling. Communication was also cited as a means to engage with students. Participant C indicated a need to communicate more with students and “be a lot more intrusive in how we provide the services and make those services known to our students.”

Participant E says, “the most important factor is to receive training on utilizing the data.” She provided the following analogy:

It’s kind of like when you learn how to drive, well, you can say to a student or a kid, you know, here’s the book, here’s the car, now go do it. But you’ve got to have training. You’ve got to have time at the wheel. You’ve got to have time navigating and that kind of goes back to the other conversation which is time. Trainings were referenced as a sub-category of communication and acted as a reminder that appropriate usage of the data analytics plays a role. Participant D felt that predictive analytics should be used for good and not “profiling” with potential negative influences. Participant D further stated “counselors will need to be…will need to re-learn their
process of how to deal with students who may predictively not do well” and use data analytics for “only positive” communication.

**Resources.** Four of the five interviewees indicated a need to designate resources according to achieving the desired outcome of increasing course completions. These resources could be staffing requirements, time availability, or institutional financial commitments. Participant A stated that the college would “target where to use its limited resources to support student retention.” Participant B stated that “providing all the necessary support they [students] need to feel like they [students] can continue and complete successfully” while allowing the college to “customize their interventions” was important. For Participant C, resources were needed in the form of an “institutional commitment to make sure that we have the planning and the strategies in place to, kind of, fully implement whatever is being produced by the software.” Participant C continued by stating:

> We need to have the programs in place to make sure that once we have the information we could effectively utilize and get to students…require a lot of resources financially…[and] human resources to make sure that we are ready to do the things we’re doing.

**Outcomes.** All five participants thought outcomes were important factors to consider when using predictive modeling to affect increases in student course completion rates. As stated by Participant A, these outcomes included “helping students meet their education goals in a timely manner” and “increased student retention.” Additionally, Participant E felt that predictive modeling has “become a resource of information” above and beyond what they normally have access to from traditional sources at their college or
district. Participant A stated a belief that outcomes were important to recognize prior to setting up a predictive modeling system as it outcomes may determine what data is needed and how that data is important to the anticipated outcomes. Another interviewee, Participant D, wanted to ensure that outcomes would be used for positive impact. In other words, she did not want a “negative profile” to exist that would inhibit the student from succeeding as a “self-fulfilling prophecy.” Further advice from Dr. Paul Dosal states:

Don’t expect the platform to solve your problems for you, it gives you the insights. As Civitas Learning’s Co-Founder Mark Milliron says, ‘It shines the light for you.’ You have to figure out what to do with it. How are you going to use this information? (Civitas, 2017, p. 7)

Inclusion. All five of the participants indicated that staff involvement, particularly faculty involvement, was an important factor in the success of predictive modeling. According to Participant A, “Faculty are involved from the beginning.” For Participant B, “one of the most important factors is that our faculty is using it…and…faculty are really engaged in this effort.” Participant C continues by stating “classroom-level faculty, they play a huge role in the overall student success concepts.” He continues by stating:

unless faculty are on board and included in the discussion and are willing to, you know, look at the pattern and how this can shift the overall outcome for students, it’s not going to be that great of a success.

Participant E commented: “We have to pull multiple people together from various disciplines.” Participant A stated: “It’s really a joint effort between instruction and
student services.” Only one interviewee, Participant D, mentioned including students in the discussion as an important factor of predictive modeling.

**Summary**

This chapter presents the data and findings from interviews, archival data, and artifacts as they related to addressing the purpose statement and research questions. Based on the analysis of the data, particularly of the themes coded as part of the interview transcripts, similar themes resonate with each of the five cases studied. Table 16 provides a summary of the research questions, the findings, and related data sources examined.

The findings for each research question are presented based on the number (frequency) of responses with a secondary significance determined by the number of participants who identified similar responses. As listed in Table 16, the findings are presented in order of significance by research question. These findings are based on coded themes identified by review of the transcribed interviews and processed using NVivo software.

Chapter V offers a summary of major findings from the analysis in Chapter IV and includes conclusions, implications, recommendations for further action, recommendations for further research, concluding remarks and reflections from the researcher.
Table 16

Summary of research questions and findings.

<table>
<thead>
<tr>
<th>RESEARCH QUESTION</th>
<th>FINDING(S)</th>
<th>DATA SOURCE(S)</th>
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</thead>
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<tr>
<td>RQ1: What was the impact of utilizing predictive modeling to improve successful</td>
<td>1. Little to no improvement of successful course completion rates</td>
<td>• Interviews</td>
</tr>
<tr>
<td>course completion rates for at-risk students at California community colleges?</td>
<td>2. Increased student contact</td>
<td>• Data Mart</td>
</tr>
<tr>
<td></td>
<td>3. Timely intervention strategies</td>
<td>• District Board Minutes</td>
</tr>
<tr>
<td></td>
<td>4. Identify and monitor students</td>
<td>• District Board Reports</td>
</tr>
<tr>
<td></td>
<td>5. Sufficient support services</td>
<td>• Civitas Learning Briefs</td>
</tr>
<tr>
<td></td>
<td>6. Successful completions and retentions to achieve educational goal</td>
<td></td>
</tr>
<tr>
<td></td>
<td>7. Institutional metrics and reporting</td>
<td></td>
</tr>
<tr>
<td>RQ2: What factors of predictive modeling have the most importance for improving</td>
<td>1. Planning and strategy</td>
<td>• Interviews</td>
</tr>
<tr>
<td>successful course completion rates for at-risk students as perceived by California</td>
<td>2. Communication and training</td>
<td>• Data Mart</td>
</tr>
<tr>
<td>community college administrators?</td>
<td>3. Resources</td>
<td>• District Board Minutes</td>
</tr>
<tr>
<td></td>
<td>4. Outcomes</td>
<td>• District Board Reports</td>
</tr>
<tr>
<td></td>
<td>5. Inclusion</td>
<td>• Civitas Learning Briefs</td>
</tr>
</tbody>
</table>
CHAPTER V: FINDINGS, CONCLUSIONS, AND RECOMMENDATIONS

Overview

The purpose of this case study was to determine the impact of utilizing predictive modeling to improve successful course completion rates for at-risk students at California community colleges. A secondary purpose of the study was to identify factors of predictive modeling having the most importance for improving successful course completion rates for at-risk students as perceived by California community college administrators. Two research questions guided this study:

1. What was the impact of utilizing predictive modeling to improve successful course completion rates for at-risk students at California community colleges?
2. What factors of predictive modeling have the most importance for improving successful course completion rates for at-risk students as perceived by California community college administrators?

A case-study approach was used, combining the collection of qualitative data in the form of personal interviews and review of artifacts along with quantitative data by reviewing archival data from five separate colleges’ CSSOs. The interview data was recorded and then transcribed prior to being entered in the NVivo software. The NVivo software assisted in tracking the data for emerging themes. Archival data for each sample college, along with data for all 113 California community colleges, were collected and placed in tables and figures for review, comparison and analyses. Archival and interview data were used to answer both research questions.

The population consisted of California community college administrators who held the position of chief student services officer (CSSO) at their respective colleges.
CSSOs were selected as these positions have oversight over services, practices and policies that may influence a student’s successful course completion. The sample population included five college administrators, three from one southern California district and two from one central California district. Further criteria to participate included a district or college purchase of the Civitas Learning, Inc. (Civitas) predictive-modeling software and/or exposure to the software and potential usage through training received and/or day-to-day usage. Five CSSOs, one from each of five colleges, were available, willing, and participated in the interviews conducted by the researcher.

**Major Findings**

A summary of the key findings that emerged from the analysis in Chapter IV is presented in this section. The findings are organized by research question and the result of information gathered during interviews and review of archival data and artifacts. The first research questions asked: What was the impact of utilizing predictive modeling to improve successful course completion rates for at-risk students at California community colleges?

1. *Little to no improvement of student successful course completion rates.* The use of predictive-modeling software was not directly tied to any improvements in successful course completion rates.

2. *Increased student contact.* Predictive-modeling software provided additional ways to increase student contact, allowing a corresponding increase in student engagement. Participants indicated that it was important for the student to have a sense of “belonging.” Based on findings of Bergman et al. (2014), “as a student felt more strongly that an institution was responsive to his or her needs, the odds
of persisting increase” (p. 98). Participant C indicated that the software may help identify a student or group of students so that an administrator may provide support services, allowing “more of a unique connection to each individual student’s needs.” Participant B indicated “that we’re really concerned about their [the students’] overall well-being” and want to “reach out to them via our counselors, via our staff, via our faculty.” A shared belief of the participants was that engaged students were more likely to seek support services and successfully complete their courses and educational goals. Further, the participants indicated that an aware student understood the importance of support services and engagement and knew how to obtain the services they needed, when they needed them. As found in the literature review, student engagement was a critical factor in student retention, course and degree completions (Beaudoin & Kumar, 2012; Bean, 1981; Bean & Eaton, 2001; Callery, 2012; Goldrick-Rab, 2010; Jenkins & Cho, 2013; Jong and Krenkel, 2013; Kelley-Hall, 2010; Smith, 2013; Tinto, 1995, 1988, 1993, 2004). As identified by Bean and Eaton (2001), student support programs should incorporate practices that increase the confidence of students in four areas by building beliefs that students are: (1) socially effective; (2) academically effective; (3) in control of their outcomes; and (4) have developed “coping skills and [are] motivated to approach academic and social challenges” (Bean & Eaton, 2001, p. 85).

3. Timely intervention strategies. Predictive modeling gave CSSOs an early alert to identify those students who may be at risk of non-completion. Timely interventions were almost as important as student engagement and awareness.
Participants commented that providing interventions after the fact did not alter the outcome—in this case, course non-completions. However, if the student could be identified and receive timely support services prior to the end of the term that help with course completion, there was a greater likelihood of the student completing the course. The literature review indicated that intrusive services were characterized as an “inescapable engagement as part of common institutional practices available to all students through the use of structured educational pathways” (CCCSE, 2014, p. 4). When administrators limit options to students through these structured pathways, students “may experience more anxiety and frustration…and, as a result, are more likely either to make a poor decision or to retreat from the situation” (CCCSE, 2014, p. 3). The administrators’ evolving role is to ensure that the policies, procedures, programs, and services offered to students at risk of non-completion are viable, timely, and appropriate (Kuk & Banning, 2009; Dorsey, 2014).

4. **Identify and monitor students.** An important impact of predictive modeling was the ability to identify students. In some instances, identifying students allowed the ability to further track or monitor students. Participants stated that predictive modeling provided an easy mechanism to quickly identify students at risk or students who are achieving their goals. Those at risk were identified to receive timely interventions. Those achieving their goals were acknowledged and congratulated (tied to engagement). Dowd (2005) suggests that college administrators continually question, analyze, and engage in professional dialogues about their data to achieve change and improvements in student success. By
encouraging administrators’ moving to data-driven decision-making using predictive-modeling tools, students identified as at risk may be provided individualized intervention strategies unique to their personal needs and experiences (Bachler, 2013; Beaudoin & Kumar, 2012; Callery, 2012; Essa & Ayad, 2012).

5. **Sufficient support services.** Information from predictive modeling helped identify the right services to provide at the right time. There was an acknowledged need for sufficient support services available to all students. Because of limited resources, they could not always help all students, even when identified as at-risk. Providing a positive college environment along with accompanying support services and practices increased students’ willingness to persist (Astin, 1999; Bean & Eaton, 2004; Kelley-Hall, 2010; Tinto, 1975, 1993 & 2004). Some of the support provided and considered beneficial by researchers are counseling and academic advising (Zhang et al., 2014), tutoring in reading, writing, and math, and helping them advance in technological skills and capabilities needed in 21st-century higher education institutions and workplaces (Bulger & Watson, 2006).

6. **Successful completions and retentions to achieve educational goals.** There was no indication that predictive modeling directly helped increase successful course completions. However, most participants did indicate it was a potentially useful resource to assist them in this goal. All but one participant named this as an outcome anticipated by using predictive modeling. Course completions are seen by Goldrick-Rab (2010) as “intermediate indicators or milestones” (p. 440) and may reflect a student’s overall progress. For community colleges, Goldrick-Rab
states that when enrollment rises, students compete for limited college resources and completion rates decrease. Because current California funding of community colleges is based largely on enrollment numbers, colleges have not, until recently, emphasized completions (Goldrick-Rab, 2010). Bulger and Watson (2006) determined by review of their research results that those students who entered college expecting to complete their educational goals and receive a credential were most likely to persist. This is in line with the conclusions drawn by Berger and Braxton (1998), recognizing that commitment to the intent of persistence is a strong motivator and factor to actually complete the student’s educational goal. While other factors were identified as important to achieve student persistence, the intention to pursue and complete an educational goal had more of a positive impact on student persistence (Bergman et al., 2014).

7. Institutional metrics and reporting. The use of data analytics provided within predictive modeling helped the CSSOs complete mandated reporting requirements. As found in the literature review, performance-based funding requirements were being established in many states (Layzell, 2007; Polatajko, 2011). As some states consider a move to performance-based funding models, both Layzell (2007) and Polatajko (2011) note that funding commitments may change depending on external influences like public perceptions of value, economic upheaval, or changing educational practices or trends. Astin (1997) believes that student course completions and degree attainments are key indicators of institutional effectiveness.
The second research question asked: What factors of predictive modeling have the most importance for improving successful course completion rates for at-risk students as perceived by California community college administrators? The CSSOs identified five factors they considered important with their efforts toward students’ successful course completion rates.

1. **Planning and strategy.** Because the data is being pulled from a variety of sources, the CSSOs believed there should be comprehensive planning to determine what data is needed, how it should be used, and if the modeling proposed is accurate. Additionally, “scrubbing” of existing data to ensure accuracy of analytic predictions was deemed an important part of this theme. As found in the literature review, the term knowledge mobilization (KMb) “indicates that this work requires specific effort, over time, working with others, and involves much more than telling people about research findings” (Levin, 2013, p. 2). Levin (2013) further suggests that KMb is an interactive multi-directional process involving people reviewing data-derived information and relating it to institutional practices.

2. **Communication and training.** Constant communication was needed to ensure all campus stakeholders were fully aware and participating. Training was also identified as a key component within this factor to ensure appropriate usage of the predictive modeling data and understanding of what it means. Calvert (2014) stated: “Predictive modeling cannot determine exactly that probability [of successful completion] but it can estimate it” (p. 170). Denley (2014) believed a “model that used the past to influence the future” (p. 66) had the potential to
perpetuate negative stereotypes and suggests that models should be built to
“safeguard against such a phenomena” (p.66).

3. **Resources.** Availability of resources was identified as an important factor when using predictive modeling to assist students with successful course completions. Resources identified were anything from personnel (staff and faculty), financial capability to provide support services, and availability of time to allocate toward learning and understanding predictive modeling. Although participants thought predictive modeling was a useful decision-making tool to identify those students potentially at risk of not completing courses, the data analysis must be accessible, reliable, usable, and understandable to benefit community college administrators (Dorsey, 2014; Marsh et al., 2006). Using these predictive models to make data-driven decisions, administrators may then create, enhance or revise policies and practices related to intervention strategies that keep students in school (Bachler, 2013; Delen, 2011-12; Keys, 2013; Whalen, Saunders, & Shelley, 2009-2010). However, participants stated that without resources to make informed decisions using predictive modeling that impact and improve successful course completion rates, the information is for naught.

4. **Outcomes.** Measurable outcomes, either realized or anticipated, were considered important factors to increase student retention and course completion rates by making informed decisions using data from predictive modeling. Successful course completions were a building block for successful academic goal completion, whether that be a certificate, degree, transfer to a four-year school, or new skills and abilities that may be applied to enhance their current employment.
Bulger and Watson (2006) determined that those students who entered college expecting to complete their educational goal and receive a credential were most likely to persist. This is in line with the conclusions drawn by Berger and Braxton (1998) recognizing that commitment to the intent of persistence is a strong motivator and factor to actually complete the student’s educational goal. While other factors, like campus culture, support services, financial capability to afford college, family and friends providing emotional support and encouragement, were identified as important to achieve student persistence, the intention to pursue and complete an educational goal had more of a positive impact on student persistence (Bergman et al., 2014). Besides completing academic goals, two participants felt an outcome would be capabilities that supported mandated reporting required by state and federal agencies.

5. **Inclusion.** A diverse collection of staff, faculty, and administrators were needed for a successful implementation of and support for predictive modeling. In particular, faculty were overwhelmingly identified as critical to providing current data, e.g., attendance in classes, that may help predict and model future behavior. Learning Management System (LMS) information systems were used in online and in-person classrooms to provide students around-the-clock access to course content, homework assignments, quizzes, and tests. The LMS helped faculty manage “interactive communication with students via messages, forums and surveys” (Naveh, Tubin & Pliskin, 2010, p.127). By accumulating detailed information on student activity in the course, these LMS systems act as a data repository of student engagement by tracking the instances of student access and
amount of time spent in the LMS. As such, the participants felt that faculty support, interaction, and understanding the importance of their data collection via LMS and other systems, were critical.

**Unexpected Findings**

The purpose of this study was, in part, to discover impacts of predictive modeling on increasing the rate of students’ successful course completions. There were two unexpected findings:

1. A surprising yet key finding is that there is no discernable improvement in successful course completion rates. The sample colleges’ self-reported successful course completion rates do not show a marked increase during the academic terms reviewed when compared to the California community college system-wide success rates.

2. An additional unexpected or surprising finding was that successful retention and completion to achieve an educational goal was not identified by all participants in the study as an impact or outcome of using predictive modeling.

As found in the literature review, course completions were viewed by Goldrick-Rab (2010) as “intermediate indicators or milestones” (p. 440) and may reflect a student’s overall progress. For community colleges, Goldrick-Rab (2010) stated that when enrollment rises, students compete for limited college resources and completion rates decrease. Because current California funding of community colleges is based largely on enrollment numbers, colleges have not, until recently, emphasized completions (Goldrick-Rab, 2010). Many administrators agree that positive outcomes should be a measurement for funding but believe that it should only be one of the many
measurements used rather than a reliance or “exclusive focus on credential completion and transfer rates” (Bailey, Jenkins, & Leinbach, 2005, p. 6).

### Conclusions

The focus of this study was to determine the impact of and identify those factors considered important, as perceived by CSSOs, to improve successful course completion rates by using predictive modeling. The findings were reviewed and placed in context with the research literature. The following conclusions can be made regarding the findings in this study:

1. Based on the research and archival data reviewed, more research is needed on this topic to determine if there is a link between using predictive modeling software and increases in successful course completion rates. Data analytics and predictive-modeling software, successfully used for years in the healthcare and defense fields, is now seen as a potential resource for higher education to identify ways to improve its completion rates and address pressure from performance-based funding initiatives. Since 2012, the California community college system has implemented several student success initiatives (Student Success and Support Program, Student Equity Program, Basic Skills, and Career Pathways to name a few) with goals to improve student degree and certificate achievement. For sample college data showing an increase in course completion rates, a direct link was not made to predictive-modeling software use or any of the other CCC student success initiatives implemented since 2012. Data analytics and predictive modeling is a new tool for higher education. As with any new resource, it may
take more time to discover its best uses before improvements to desired outcomes are seen.

2. Based on the findings in this study and supported by the literature, a diverse population of college stakeholders needs to jointly determine the outcomes desired from and identify the data needed to accurately analyze and model predictions. Predictive-modeling software is a tool and cannot be expected to solve a college’s problems. Instead, this tool helps illuminate the issues. A team of stakeholders is needed to figure out what data to collect and analyze, what the data is saying and what to do with that information. An early user of Civitas Illume, Dr. Paul Dosal, Vice President of Student Affairs and Student Success at the University of South Florida, stated: “People at all levels of this organization are at this table using Illume and contributing to the committee’s work and development in a democratic, dynamic and inclusive process” (Civitas, 2017, p. 4). Strategies are informed by data and outcomes are measureable. According to Sa, Li, and Faubert (2011), college and university faculty and staff have overall positive views toward evidence and information driving practices and policy. However, Sa et al. (2011) report that while there is support, there are also perceived or actual barriers for its implementation. The barriers identified included lack of time, lack of measurable outcomes established, lack of research and technological resources, and too many diverse initiatives with competing data needs (Sa et al., 2011).

3. Based on the findings in this study and supported by the literature, policy decisions should start with data. As part of this culture of data first, clear
guidelines and standards of evidence should be set. Besides identifying students early who may be at risk of non-completion, colleges may develop more personalized services and support to “reach out to the right students, with the right message, at the right time” (Civitas Learning Inc. [Civitas ATD], 2017, p. 2). Predictive modeling is in early stages of use and development at California community colleges. With any new initiative, time is needed to identify, develop and refine the use of predictive modeling and determine benefits based on insights obtained from it.

4. Based on the findings in this study and supported by the literature, administrators need assistance with and exposure to data analytics and predictive modeling as they move to a data-driven decision-making culture. Predictive modeling transforms the culture of working with students toward successful course completions and educational goal achievements. Data is added cumulatively to the predictive-analytics model. There must be constant review and discussion to determine if revisions to the model are needed. Predictive modeling is a dynamic process. This type of data modeling can predict college student behaviors as a collection of items that lead to a particular outcome (dropping out) (Bailey & Alfonso, 2005; Beaudoin & Kumar, 2012). However, if the data used to model or predict behaviors and outcomes are incomplete or are not significant predictors of course completion, the ability to predict outcomes may be limited. Predictive modeling can identify positive outcomes, such as staying in college, as well as make determinations that would indicate at-risk behaviors (Dorsey, 2014).
results of this modeling may then be used to provide interventions to prevent dropping out (Bailey & Alfonso, 2005; Beaudoin & Kumar, 2012; Dorsey, 2014).  

5. Based on the findings in this study and supported by the literature, an impact of using predictive modeling may cause administrators to change or re-focus intervention and support services to increase student engagement for those students identified as at risk of non-completion. The information provided from using predictive modeling identified individuals or groups of students who may need help. The administrators using this tool needed to make policy and process changes. The changes would include, along with other services, a more intrusive model of advising and engagement. These services would nudge and prod the student toward successful completion of courses. There is a need to shift strategy and make a cultural change to provide students with a sense of belonging and knowing that the college personnel believes in every student’s ability to succeed. As found in the literature review, student engagement and awareness play important roles in student retention and course completions. Engagement provides an opportunity for a self-fulling positive outcome, one of successful course completions. Establishing intrusive and consistent touch points with students encourages them to succeed. Adelman (2006) argues that the first year is critical to achieving student behaviors by providing consistent academic advising, checking-in points with faculty and staff, multiple measures for assessment, and, for some students, a decreased credit load in the first year. Whalen, Saunders, and Shelley (2009-2010) found in their research that the implementation of learning communities greatly increased one-year retention rates as it was a means “to assist
students with both academic and social engagement at the institution” (p. 425).

After the first year, additional variables and indicators, like good grades, consistent attendance and motivation, identify those students with or without intentions to complete their educational goals (Astin & Oseguera, 2005; Whalen et al., 2009-2010). Each group of students needs support practices throughout the educational journey.

6. Based on the findings in this study and supported by the literature, a culture and cycle of continuous review and improvement should be encouraged and established. Institutional strategic goals need to be fully integrated into regular performance tracking tied to key performance indicators. Through continuous review by a diverse population of stakeholders, new data sources may be found and used to refine insights provided from predictive modeling software.

**Implications for Action**

In reviewing the findings and establishing conclusions, several implications for further action were identified. The following are recommendations for further action:

1. A thorough analysis of outcomes desired and alignment with strategic goals should be considered prior to committing resources, funding and personnel, to purchase or create data-analytic and predictive-modeling software. Without sufficient preparation, training, and expectations of use within the culture of the institution, the software may become a forgotten or little-used tool.

2. Revise all job descriptions and performance evaluations to include language that reflects a data-driven culture of informed decision-making, customer-service
management and engagement, performance outcomes tied to key performance indicators, and shared communications.

3. Create a case-management approach to student support services. As one of the interview participants stated: “Building a comprehensive response consists of student services and academic affairs working together as a holistic response [unit] to at risk students.” The community of support may be within a college, within a district, or include stakeholders from multiple disciplines or from many institutions. Knowledge distribution may occur via email listservs, blogs, Facebook pages, or regular meetings (virtual or in-person) to allow time for discussion of concerns and learning opportunities for participants. This concept includes that everyone has a starting point for information and can learn from others and their experiences. Civitas (2017) suggested learning from healthcare case-management approaches to create staff and faculty “care teams [who] use data to improve their interactions with students” (p. 5).

4. Create a learning academy. By sharing expertise, both experienced and new staff can help each other address concerns or issues around data-driven decision-making. An academy would provide information on strategies to address topics like:
   a. Evaluation design
   b. Data collection
   c. Data analysis and interpretation
   d. Communication and reporting
   e. Evaluation management
f. Cyclical review for continuous improvement

5. Provide open access for all employees to non-identifying student information and behaviors with the purpose of assessing and improving successful course completion rates. This expands involvement by the community and makes student success part of each employee’s duties and responsibility. New or different insights may be achieved by broadening the exposure to predictive-modeling information.

6. Create an institutional data standards committee. The committee would set standards of data use and establish a common data-element dictionary within the institution. This oversight allows a common language between systems and data repositories so that the data are not subject to misuse or potential misinterpretation.

7. Tie funding to creativity and innovation. If data validates that something is working, create a mechanism to allow funding (dollars) to follow the data.

8. Create a regional support center. The California community college system is divided into ten formalized regions. Each region could create a support center that provides mentoring, discussions to consider when looking at data and models, positive and negative impacts, how to translate data into services, to name a few. Regular meetings and topics can be posted and available online. There are opportunities for colleges or districts within a region to host the support center.

9. Develop data-focused workshops and conferences. Either encourage creating specific workshops or conferences, or suggest existing organizations incorporate data-focused sessions into their programs.
10. Provide professional development opportunities. Encourage participation in associations that provide professional development and learning opportunities related to trends in using and understanding data-driven processes.

11. Support vendor-provided user groups. Encourage participation and provide incentives for continuous learning of the product used at the institution. Many vendors provide an opportunity for annual meetings that provide learning opportunities about the product and how it is being used at other higher education institutions. According to Dr. Dosal at USF, “we are all learning from each other as we do this work” (Civitas, 2017, p. 6).

**Recommendations for Further Research**

This study examined factors and impacts of predictive modeling related to students’ successful course completion rates for California community colleges and as perceived by five chief student service officers within that system. The following are recommended to further this research:

1. Repeat this study in three to five years. This study looks at the use of predictive modeling in its infancy within the California community college (CCC) system. By repeating the study, the additional time allows for building experience with the concepts, broadens data availability, and may identify how predictive modeling works as part of a toolset to directly increase successful course completion rates.

2. Repeat this study in several years and disaggregate rates of success by modes of course delivery. This study reviewed all degree-applicable and transferable credit courses delivered by any mode. By disaggregating rates of success by...
modality, it may be possible to reach new or different findings and conclusions.

3. Expand the study to include more CCC personnel beyond administrators.

4. Expand the study to include more districts and colleges within the CCC system.

5. Expand the study beyond the state of California.

6. Conduct a quantitative study on the correlation between success rates and the use of predictive modeling at a college.

7. Conduct a study to include other predictive-modeling software solutions.

8. Conduct a study to determine if a correlation exists between experience of the CSSO and the use of predictive modeling with student interventions.

9. Conduct a study to determine those data elements and sources that best correlate to data analytics and predictive modeling of future student behavior.

Concluding Remarks and Reflections

This study provided findings and recommendations on the use of predictive modeling toward successful course completions for at-risk students. Predictive modeling has been used successfully in other professions, e.g., defense, military, and health occupations. However, predictive modeling usage to support student success is still in its infancy within higher education, particularly in community colleges. We must also remember that data analytics and predictive modeling is a tool and is only as good as the data that goes into it. Only through continued review, evaluation, and improvements will the tool become a valuable resource to help correctly identify students who need assistance in order to succeed.

Community colleges have lots of data and add to it daily. When all users have access to non-identifying information about students and can easily access how that
information ties to institutional key performance indicators, those staff members become more engaged. This engagement may then lead to increased levels of staff participation in planning processes. Through participation, staff build more ownership of the results desired and achieved. As with any culture shift, this change to one of data-driven decision-making may take years to fully develop. Strong and experienced leadership is needed to support this cultural change.

As an administrator in the California community college system, I understand and recognize the importance of students taking responsibility for their actions. However, I believe we need to bring hope to students who may not believe in themselves by providing support services that will engage them and bring a sense of belonging to the campus. I also understand that it takes some grit to pave one’s own path. My hope is that this research provides the seed to expand on the topic of predictive-modeling utilization as a tool to increase successful course completion rates. As one of my interviewees said, and I paraphrase, let it be used for the good of the student.
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## APPENDIX A

### Literature Review Synthesis Matrix

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<th>Citation</th>
<th>HE Completion Agenda</th>
<th>State Completions</th>
<th>Accountability</th>
<th>Comm. College Role</th>
<th>Student Persistence</th>
<th>Student Engagement</th>
<th>Students At-Risk</th>
<th>Course Completion</th>
<th>Administrator Role</th>
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<th>Retention/Completion</th>
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APPENDIX B

Interview Script and Questions

Introduction

Thank you for agreeing to participate in this interview. My dissertation research for the doctorate in Organizational Leadership at Brandman University includes interviewing administrators who are utilizing predictive modeling to improve course completion rates for students at California community colleges to determine the impact this may have on outcomes. I am also interested in hearing your perceptions of those factors you believe are most important for improving course completion outcomes by using predictive modeling. As a reminder, your informed consent allows you to refuse to participate or withdraw from this study at any time without any negative consequences.

This interview is scheduled for 60 minutes and is semi-structured—meaning that I have a list of structured questions allowing flexibility for follow-up questions, as needed, for clarification or additional information.

All information related to this study remains confidential. All data will be reported without reference to a specific individual or institution. Please feel free to stop me at any time if you would like to discontinue the interview. You may also ask that I skip a particular question or choose not to answer any of the questions. Your comfort during the interview is my primary concern.

I will be recording the interview for later transcription to ensure accuracy of data collected. Once transcriptions are available, I will provide you with a copy for your review and any edits you would like to communicate to me.

Do you have any objections to my recording the interview?

Do you have any questions before we begin? Let’s begin.

Demographic Information

Let’s start with some demographic information:

1. I want to make sure I have your position title correct. You are the [position title]
2. How long have you been in your current administrative position here at ______ college?
3. What predictive-modeling software do you use?
4. When did you start using predictive-modeling software here at your college/district?
Specific to the study

1. I am defining successful course completions as those with a passing letter grade. Why are improving successful student course completions important?

2. What outcomes did you have in mind or expect by using this software?
   a. What outcomes were realized?
   b. Of those not realized, why do you believe they did not happen?
   c. Were there outcomes that surprised you?
      i. What were they?

3. How does using predictive-modeling software make a difference in successful course completion rates?

4. In your opinion, what factors do you consider most important when utilizing predictive-modeling software to impact successful course completions?

5. Were there factors you thought would be important or helpful but were unable to use with your predictive-modeling software?
   a. If so, what were they and why couldn’t you use them?

6. Once you identify students at risk of not completing courses, what types of things are you doing at the college or district to improve successful course completions for those students?
   a. Would you describe how the software assisted in those efforts?
   b. What are those improvements?

7. What lessons have you learned from using predictive-modeling software?

8. As you move forward, what are your plans for using this software in the future?

9. What advice would you give to other college or district administrators interested in implementing predictive-modeling software?

10. Do you have anything further you would like to add at this time?

Conclusion

Thank you again for your time and thoughtful consideration of this research study today. As I mentioned previously, this interview will be transcribed but anonymous. I will send you a copy of the interview transcript for your review and comments back to me. You are more than welcome to contact me if you would like to add anything further to your comments today. If you would like a copy of my final approved dissertation, please let me know and I will be happy to share it with you.
APPENDIX C

Alignment of Interview Questions with Research Questions

<table>
<thead>
<tr>
<th>Purpose</th>
<th>Interview Script</th>
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<tr>
<td>The purpose of this case study was to determine the impact of utilizing predictive modeling to improve course completion rates for at-risk students at California community colleges. A secondary purpose of the study was to describe which factors of predictive modeling have the most importance for improvement of course completion rates as perceived by California community college administrators.</td>
<td>Introduction, Informed Consent, Research Participant’s Bill of Rights, Demographic Information Verification, Interview Questions, Concluding Statement</td>
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<thead>
<tr>
<th>Research Question</th>
<th>Interview Questions</th>
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<tr>
<td>Research Question 1: What was the impact of utilizing predictive modeling to improve course completion rates for at-risk students at California community colleges?</td>
<td>Interview questions 2, 3, 6, 10</td>
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<td>2. What outcomes did you have in mind or expect by using this software?</td>
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<td>b) What are those improvements?</td>
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<td>10. Do you have anything further you would like to add at this time?</td>
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<td>Research Question</td>
<td>Interview Questions</td>
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<tr>
<td>Research Question 2:</td>
<td><em>Interview questions 1, 4, 5, 7, 8, 9, 10</em></td>
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<tr>
<td>What factors of predictive modeling have the most importance for improvement of course completion rates as perceived by California community college administrators?</td>
<td>1. Why are improving student course completions important?</td>
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<td>4. In your opinion, what factors do you consider most important when utilizing predictive-modeling software to impact course completion?</td>
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<td>5. Were there factors you thought would be important or helpful but were unable to use with your predictive-modeling software?</td>
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APPENDIX D

Brandman University Institutional Review Board Approval

<table>
<thead>
<tr>
<th>BRANDMAN UNIVERSITY INSTITUTIONAL REVIEW BOARD</th>
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<tr>
<td>IRB Application Action – Approval</td>
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<td>Date: January 31, 2017</td>
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Name of Investigator/Researcher: Rita D. Grogan

Faculty or Student ID Number: B00486919

Title of Research Project:
California Community College Administrators’ Use of Predictive Modeling to Improve Student Course Completions

Project Type: [ ] New [ ] Continuation [ ] Resubmission

Category that applies to your research:
[ ] Doctoral Dissertation EdD
[ ] DNP Clinical Project
[ ] Masters’ Thesis
[ ] Course Project
[ ] Faculty Professional/Academic Research
[ ] Other:

Funded: [ ] No [ ] Yes

Project Duration (cannot exceed 1 year): One year

Principal Investigator's Address: 7602 Sunlit Oaks Ct, Gilroy, CA 95020

Email Address: rrgrogan@mail.brandman.edu Telephone Number: (408) 832-1655

Faculty Advisor/Sponsor/Chair Name: Dr. Tod A. Burnett

Email Address: toburnet@mail.brandman.edu Telephone Number: (562) 972-1884

Category of Review:
[ ] Exempt Review [ ] Expedited Review [ ] Standard Review

Brandman University IRB Rev. 11-14-14 Adopted November 2014
I have completed the NIH Certification and included a copy with this proposal.
NIH Certificate currently on file in the office of the IRB Chair or Department Office.

Signature of Principal Investigator: Rita Grogan  
Digitally signed by Rita Grogan  
Date: 2017.01.31 21:44:25  
Date: January 31, 2017

Signature of Faculty Advisor/ Sponsor/Dissertation Chair: Tod A. Burnett  
Digitally signed by Tod A. Burnett  
Date: 2017.02.01 06:21:54  
Date: January 31, 2017
BRANDMAN UNIVERSITY INSTITUTIONAL REVIEW BOARD
IRB APPLICATION ACTION – APPROVAL
COMPLETED BY BUIRB

IRB ACTION/APPROVAL

Name of Investigator/Researcher: Rita Grogan

☐ Returned without review. Insufficient detail to adequately assess risks, protections and benefits.

☑ Approved/Certified as Exempt form IRB Review.

☐ Approved as submitted.

☐ Approved, contingent on minor revisions (see attached)

☐ Requires significant modifications of the protocol before approval. Research must resubmit with modifications (see attached)

☐ Researcher must contact IRB member and discuss revisions to research proposal and protocol.

Level of Risk: ☐ No Risk ☑ Minimal Risk ☐ More than Minimal Risk

IRB Comments:

Tim Perez

IRB Reviewer:

Telephone: __________________________ Email: __________________________

BUIRB Chair: Doug DeVore

Date: 2/9/2017

REVISED IRB Application

☐ Approved ☐ Returned

Name: ____________________________

Telephone: __________________________ Email: __________________________ Date: __________________________

BUIRB Chair: ____________________________

Brandman University IRB Rev. 11.14.14 Adopted November 2014
APPENDIX E

Sample Email Requesting Participation

Date

Dear [Potential Study Participant],

My name is Rita Grogan and I am currently a doctoral candidate at Brandman University in the Organizational Leadership program. Your colleague, [insert sponsor’s name], provided me with your contact information. I am conducting a research study that explores the impact of using predictive modeling to improve student course completion rates in the California community college system. Additionally, this study describes those factors of predictive modeling having the most importance for improvement of course completion rates as perceived by California community college administrators. The proposed study is needed for a better understanding of data-driven decisions, specifically predictive modeling, as used by administrators to increase student persistence. Findings from the study will provide information on promising practices to improve student persistence that may be transferred for use by other administrators.

I am asking your assistance in the study by participating in an interview which will take from 30 to 60 minutes and will be set up at a time and day convenient for you. If you agree to participate in an interview, you may be assured that it will be completely confidential. No names will be attached to any notes or records from the interview. All information will remain in locked files accessible only to the researcher. No one from your college will have access to the interview information. You will be free to stop the interview and withdraw from the study at any time. Further, you may be assured that the researcher is not in any way affiliated with your college.

To participate, please contact me at (408) 832-1658 or by email at rgrogan@mail.brandman.edu to schedule a time and date for an interview that works best for you. The interview should not require more than 60 minutes to complete. I am including a copy of the participant’s bill of rights as well as a sample informed consent document.

If you have any questions or concerns about this study, please contact me at (XXX) XXX-XXXX or email me at xxxxxxxx@mail.brandman.edu. You may also contact my dissertation supervisor, Dr. Tod A. Burnett, at xxxxxxxx@brandman.edu or via phone at (XXX) XXX-XXXX with questions or concerns.

Let me know within the next 10 days of your decision. I appreciate your consideration of participating in this study and look forward to hearing from you.

Sincerely,
Rita Grogan
Doctoral Candidate, Organizational Leadership, Brandman University
APPENDIX F

Sample Informed Consent Document

Date: ________________________________

Information About: California Community College Administrators’ Use of Predictive Modeling to Improve Student Course Completions

Responsible Investigator: Rita Grogan

Purpose of Study

The purpose of this case study is to determine the impact of utilizing predictive modeling to improve course completion rates for at-risk students at California community colleges. A secondary purpose of the study is to describe which factors of predictive modeling have the most importance for improvement of course completion rates as perceived by California community college administrators.

This research explores the utilization of data-mining and predictive analytic reports that support informed decision-making leading to improved practices toward student retention and completion. By encouraging a move to data-driven decision-making using predictive-modeling tools, students could benefit from individualized intervention strategies unique to their personal needs and experiences. The findings from this research may encourage other administrators to continually question, analyze, and engage in professional dialogues about their data to improve student course completion rates. This study will increase the body of knowledge related to community college administrators and their data-driven decision-making to increase student persistence toward completion.

By participating in this study, I agree to participate in a one-on-one interview with the researcher. The interview will last between 30 to 90 minutes. Completion of the interview will take place by 90 minutes.

I understand that:

a) There are minimal risks associated with participating in this research.

b) I understand that the Investigator will protect my confidentiality by storing any research materials collected during the interview process in a locked file drawer to which only the researcher has access.

c) The possible benefit of this study to me is that my input may help add to the research regarding how administrators use predictive modeling to increase student course completions. An added benefit may describe factors of predictive-modeling software considered most important to improve course completions as
perceived by California community college administrators. The findings will be available to me at the conclusion of the study.

d) I understand that I will not be compensated for my participation in this study.

e) Any questions I have concerning my participation in this study will be answered by Rita Grogan. She can be reached by email at xxxxxxx@mail.brandman.edu or by phone at XXX-XXX-XXXX. Alternatively, you may contact Rita’s committee chair, Dr. Tod A. Burnett, who acts as co-principal investigator on this study, by email at xxxxxxx@brandman.edu or by phone at XXX-XXX-XXXX.

f) I understand that the interview will be audio-recorded. The recordings will be available only to the researcher, and will be used to capture the interview dialogue and to ensure the accuracy of the information collected during the interview. All transcripts and notes taken by the researcher during the interview will be securely stored to assure confidentiality. After the study is complete and the transcripts and notes are no longer needed, all materials will be shredded or destroyed.

My participation in this research study is voluntary. I understand that I may refuse to participate in or I may withdraw from this study at any time without negative consequences. Also, I may ask the investigator to stop the interview at any time. I understand that no information that identifies me will be released without my separate consent and that all identifiable information be protected to the limits allowed by law. If the study design or the use of data is changed, I will be so informed and my consent obtained. I understand that if I have any questions, comments, or concerns about the study or the informed consent process, I may write or call the Office of the Executive Vice Chancellor of Academic Affairs, Brandman University, at 16355 Laguna Canyon Road, Irvine, CA 92618 Telephone (949) 341-7641.

I acknowledge that I have received a copy of this form and the Research Participant’s Bill of Rights. I have read the above and understand it and hereby consent to the procedure(s) set forth.

__________________________________________________ ______________________
Signature of Participant or Responsible Party Date

__________________________________________________ ______________________
Signature of Principal Investigator Date
APPENDIX G

Sample Participant Bill of Rights

BRANDMAN UNIVERSITY INSTITUTIONAL REVIEW BOARD

Research Participant’s Bill of Rights

Any person who is requested to consent to participate as a subject in an experiment, or who is requested to consent on behalf of another, has the following rights:

1. To be told what the study is attempting to discover.

2. To be told what will happen in the study and whether any of the procedures, drugs or devices are different from what would be used in standard practice.

3. To be told about the risks, side effects or discomforts of the things that may happen to him/her.

4. To be told if he/she can expect any benefit from participating and, if so, what the benefits might be.

5. To be told what other choices he/she has and how they may be better or worse than being in the study.

6. To be allowed to ask any questions concerning the study both before agreeing to be involved and during the course of the study.

7. To be told what sort of medical treatment is available if any complications arise.

8. To refuse to participate at all before or after the study is started without any adverse effects.

9. To receive a copy of the signed and dated consent form.

10. To be free of pressures when considering whether he/she wishes to agree to be in the study.

If at any time you have questions regarding a research study, you should ask the researchers to answer them. You also may contact the Brandman University Institutional Review Board, which is concerned with the protection of volunteers in research projects. The Brandman University Institutional Review Board may be contacted either by telephoning the Office of Academic Affairs at (949) 341-9937 or by writing to the Vice Chancellor of Academic Affairs, Brandman University, 16355 Laguna Canyon Road, Irvine, CA, 92618.