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Blended Learning and Bottlenecks in the California State University System: An Empirical Look at the Importance of Demographic and Performance Analytics

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BLENDED LEARNING AND BOTTLENECKS IN THE
CALIFORNIA STATE UNIVERSITY SYSTEM: AN EMPIRICAL LOOK AT THE
IMPORTANCE OF DEMOGRAPHIC AND PERFORMANCE ANALYTICS

by

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ABSTRACT

In Fall 2014 over 460,000 students enrolled in the 23-campus California State University system; unfortunately, more than 20,000 qualified applicants were denied admission due to capacity and budgetary constraints. In response to continued overcrowding, the Chancellor's Office and Board of Trustees are investigating "bottlenecks," defined as anything limiting students' ability to graduate in a timely manner. Blended learning, a pedagogy combining face-to-face and computer-mediated instruction, presents a potential solution to alleviate overcrowding and bottleneck problems.

In an effort to investigate the extent to which student demographics and performance analytics explain student success outcomes in a popular blended learning psychology course, an explanatory sequential design was used to study 18,254 students enrolled in the course between 2006 and 2014. In the initial quantitative part of the design, logistic regression and traditional regression analysis were used to determine the predictors of those who chose to drop the course, those who ultimately passed the course, and then to investigate why some students received higher grades than others. Results revealed that race, gender, age, socioeconomic status, and early course participation were key predictors of success.

Some of the most significant findings – which included the fact that Mexican American, African American, and Filipino students were less successful in the course than their White counterparts – were examined in more detail in the qualitative part of the study that followed. Specifically, students who self-identified within these race/ethnicities provided a nuanced look at their own course experiences by completing

questionnaires and interviews for the study. Thematic findings revealed socioeconomic status, time management, parents' education, and students' campus community as factors contributing to course performance.

This study represents one of few large-scale analyses of a blended learning environment focused upon learner outcomes, and it serves to inform the evaluative work surrounding student success interventions, including the ability to predict and understand student risk characteristics for dropping, failing, or performing poorly within a blended learning environment. Understanding the many reasons students engage in less successful behavior may inform student success strategies and alleviate bottlenecks, especially as the prevalence of blended learning courses increases within the California State University system.

DEDICATION

For California State University students, past, present, and future

ACKNOWLEDGMENTS

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CHAPTER ONE

BACKGROUND AND PURPOSE OF THE STUDY

Two trends are increasingly visible within California's publically funded higher education landscape. The first is the growing demand for university admission together with diminishing funding for higher education (Vogel, 2013). Currently in California, four out of five college students attend an institution within one of the three California State higher education systems: the University of California (UC), California State Universities (CSU), and the California Community Colleges (CCC) (Johnson, 2014), and admissions and course enrollment demands outweigh the capacity to accommodate students within these institutions (California State University, 2015a).

When an undergraduate major or a campus receives applications from more qualified applicants than there are spaces in a program of study or within the entire institution, an impacted designation is assigned to the major or the campus (CSU, 2015a). Currently, every undergraduate major offered at five of the 23 California State University campuses are impacted, and according to the CSU, these same five campuses have also exhausted maximum enrollment for faculty and institutional resources (CSU, 2015a; CSU, 2015b). When supply and demand enrollment issues occur at the course level, a "bottleneck" also occurs, slowing student progress toward graduation (California State University Board of Trustees, 2013; The California State University Office of the Chancellor, 2013).

The second trend within public higher education in California is the rapidly growing implementation of blended and online instructional methods (Graham,

Woodfield, & Harrison, 2013; California State University Board of Trustees, Standing

Committee on Educational Policy, 2013). In essence, blended learning combines "face-

to-face instruction with computer-mediated instruction" (Bonk, & Graham, 2006). After

years of more traditional brick and mortar learning, rapid technological developments are

dramatically changing the face of higher education. For example, online learning

opportunities have now manifested themselves within many traditional higher education

settings (Owston, 2013) and have alleviated some of the demands upon physical campus

environments. An important example was in 2013 (Vogel), when the CSU system began

formal initiatives to explore solutions for overcrowded campuses through the

implementation of blended learning courses and innovative online technologies (The

California State University Office of the Chancellor, 2013).

Trend One: Overcrowding Within the California State University System

California State University system's 23 campuses received 344,894 completed

student applications for 2014-15 admission, 272,749 of whom were admitted and 141,420

enrolled (CSU, 2015c). Incoming 2014 students included 64,254 first time freshman,

51,524 transfer students, 20,690 graduate students, and 4,952 transitory (visiting)

students. See Appendix A for a complete report of CSU applications and admission data.

Enrollment across the 23 CSU campuses during the 2014-15 academic year totaled

460,200 students (2015). Not surprisingly, each year first time freshman and transfer

student growth in the public California systems creates greater demand for individual

course placement and overall student admission to the institutions.

A majority of the students who apply to CSUs come from within California,

creating a statewide systemic impact. For example, in 2014 California Community

College students represented 92 percent or 47,418 of the total 51,524 undergraduate transfers to CSU campuses (CSU, 2015d). Of course, demand does not stop with the CSU campuses. The California Community College Chancellor's Office reported nearly 500,000 students were wait listed for classes within the 112 two-year campuses in 2012 (Bohn, Reyes, & Johnson, 2013).

California State University bottlenecks. Courses with more student demand than there are faculty or institutional accommodations are officially termed bottlenecks, and are defined as, "Anything that limits a California State University (CSU) student's ability to make progress toward a degree and graduate in a timely manner" (California State University Board of Trustees, 2013; The California State University Office of the Chancellor, 2013). When bottlenecks occur, they can slow study cycles for students and keep others from enrolling in required classes for semesters or even years (California State University Board of Trustees, 2013).

Systemwide identification and classification of CSU bottlenecks began in 2013 (California State University Board of Trustees, 2013; The California State University Office of the Chancellor, 2013). Bottlenecks stem from a variety of systemic issues. The CSU Chancellor's Office identified and prioritized four types of bottlenecks for analysis and action throughout the 2013-14 academic year (Smith & Hanley, 2013); these include student readiness and curricular bottlenecks, place-bound bottlenecks, facilities bottlenecks, and advising and scheduling bottlenecks.

Student readiness and curricular bottlenecks. When students are not prepared to take a particular course student readiness and curricular bottlenecks can occur. Unfortunately, all students are subject to this type of bottleneck (California State

University Board of Trustees, 2013; The California State University Office of the Chancellor, 2013). Students who retake courses in an attempt to receive a higher grade after poor performance or course withdrawal add to the bottleneck problem (Smith & Hanley, 2013).

Place-bound bottlenecks. When students are required to wait for specific course offerings place-bound bottlenecks can occur (Smith & Hanley, 2013). For example, a biology department may offer a required upper-division course once a year during the fall semester; if a student in the student's final year of study is unable to secure a place within the course, that student may not be able to finish his or her studies until the following fall semester.

Facilities bottlenecks. There is a finite amount of classroom and laboratory space on a college campus. When the space and times for class offerings are booked, student demand for course sections may persist but accommodations are not available. Again, laboratory spaces and large lecture classes often fall into this bottleneck category (Smith & Hanley, 2013).

Advising and scheduling bottlenecks. Lack of student preparedness can also cause bottlenecks. When a student is not aware of, or does not follow recommended academic advising for efficient course planning, bottlenecks could occur. The slowing of course study happens when a student cannot get into a class, the student needs to graduate, or when a course is not offered in the semester the student needs to take the course (Smith & Hanley, 2013). However, the CSU has implemented a number of strategies to use technology in support of student success with bottlenecks in mind. An online eAdvising tool is available directly to students on some campuses and exclusive to

faculty and advisors to share with their students and advisees on other campuses (Course Redesign with Technology, 2013).

Trend Two: Transition to Blended Learning Pedagogy

As mentioned above, the second trend is the explosion of blended learning pedagogy in both K-12 and higher education. Blended learning for the purpose of this study is defined as the combination of "face-to-face instruction with computer-mediated instruction" and is positioned within the literature as part of the "ongoing convergence of two archetypal learning environments" (Bonk, & Graham, 2006, p. 5). Moving away from centuries of face-to-face classroom teaching methods and towards new ways of learning is now possible with the emergence of sophisticated digital content delivery and affordable, portable, and increasingly efficient devices.

Alongside technological advances, student priorities and demographics are also changing. Increased demands outside of the classroom including work and family commitments compete with the increased value of a college degree in the workplace (Johnson, 2014). The confluence of digital learning options within a traditional university environment, and the ability to access education without being physically present in the classroom for each lesson make blended learning options attractive to students. Higher education learners – especially the rising number of non-traditional students over 25 years of age – are now able to access education because of the malleable learning schedule many blended learning course formats offer (Chronicle of Higher Education Almanac, 2012; U.S. Department of Education, 2012; Dziuban, Moskal, & Hartman, 2005).

Blended learning beginnings. Delivering educational content electronically is not a new concept. Distance learning has enabled colleges to reach out beyond campus boundaries for years to access students located on outlying campuses through video, audio, or closed circuit television (Garrison, 1985). Although this was certainly one way to teach from a distance, learners still had to visit a local campus or designated facility to engage with the content. Taken together, distance learning is half of the blended learning framework, the other half being traditional face-to-face instruction.

Distance learning has changed over time, with each new generation building on the one preceding it and offering new capabilities for learning and instruction (Garrison, 1985). For example, distance learning progressed to a distributed learning environment when computers began to add off-campus independence to course instruction (1985). Earlier generations of distance and distributed learning yielded forecasts for the potential of future digital learning. Higher education technology strategy advocates looked at the digital learning trajectory and saw the potential for a "mega-university" nearly 20 years ago, citing lower cost per student with higher service capacity and global reach (Daniel, 1997).

As blended learning takes shape, researchers have worked to assign terms and meaning to the practice. In addition to a general definition of blended learning, specific detail is assigned to note the different combinations that may comprise a blended course offering. To do this Bonk and Graham (2006) use four elements, called learning interactions; these include: space, time, fidelity, and humanness. Books and articles written on the topic of blended learning tend to focus on the ongoing effort to define its characteristics, best practices, and examples of blended learning environments. Research

also indicates that work needs to go beyond the formulation of blended learning

definitions and models, to include theoretical underpinnings and empirical research

(Halverson, Graham, Spring, & Drysdale, 2012; Taplin, Kerr, & Brown, 2013).

Learning analytics and learning management systems. The National Survey

of Student Engagement (NSSE) is beginning to hone in on predictors of student success

and the role of technology in learning. For example, a large-scale survey measured

31,000 students at 58 institutions and discovered positive correlations between several

NSSE measures such as course management technology and self-reported student-faculty

interactions; high-tech communication and level of academic challenge; and

communications with the use of course management systems (National Survey of Student

Engagement, 2009; Moller, L., & Huett, J. B. (Eds.), 2012). The NSSE measures self-

reported responses in order to understand how, when, and why college students are

engaged, but learning analytics allow students, faculty and researchers to look at the

entire picture including when students become disengaged and perhaps creating

predictive models to alert pending disengagement.

Learning analytics has become popular in part by the large amount of data

generated in blended and online courses. Although there are many questions and few

simple answers in this emerging field, the premier research forum, Society for Learning

Analytics Research (SOLAR), has only hosted five conferences to date – underscoring

the nascence of the practice (Society for Learning Analytics Research, 2015). The power

and potential of learning analytics is certainly one of the reasons for the growing attention

recently dedicated to researching, understanding, and applying analytics to education. An

additional reason for the growing demand of learning analytics research and

understanding is the spike in student interactions with learning management systems. Data from student, instructor, and content interactions are captured by the system and now institutions have a conduit for putting the data to work to observe and create interventions to support student success.

Course management systems (CMS), also known as learning management systems (LMS), are increasingly present in blended learning environments as they enable faculty to use blended learning methods and measure real time outcomes (Graham, Woodfield, & Harrison, 2013). More specifically, higher education institutions' learning management systems are where course activities, readings, quizzes, and assignment submissions are typically housed and communicated between faculty and students (2013). One business in particular, Blackboard, has centered its focus on the rapid uptake of learning management systems in both K-12 and higher education.

Blackboard was founded in 1997 and today is the industry leader in classroom management software (Rivard, 2013). When students interact with the Blackboard Learning Management System, enormous amounts of data are generated, capturing login times, time spent online, the exact time students submit assignments, and how often they interact with other students. After amassing these data among thousands of institutions Blackboard was recently able to identify indicators of individual student behaviors and success. These measures are packaged and accessible on the front end of the software, providing instructors with predictive at-risk student alerts (Blackboard, 2014).

Problem Statement

The steady year-to-year increase in the number of students pursuing a university education within California's public institutions continues to exacerbate the CSU

bottleneck course problem, prolonging student time to graduation (Vogel, 2013). At the same time, research points towards the benefits that blended learning pedagogy provides learners and institutions, among them expeditious course completion timelines. Benefits described in the blended learning literature highlight the convenience of offsite classes, flexible time tables, and personalized lessons to support a range of student learners (Bonk, & Graham, 2006). The CSU Chancellor's Office in partnership with CSU campuses has begun implementing blended learning classes to help remedy bottlenecks with the goal to continue providing students with quality instruction (2013).

Benefits of blended learning are often cited but the costs are underrepresented in the literature preventing a balanced analysis of the fiscal landscape, traditional and online classroom environment, evaluation of learner outcomes, and lived experiences of both students and faculty (Taplin, Kerr, & Brown, 2013; C. Graham, personal communication, July 9, 2013). In the case of bottlenecks on California State University campuses, the courses are finished and students are gone before many struggling students are identified and interventions can take place, but one benefit of blended learning is the online and real-time transactional value of student performance, an under researched area for a number of reasons (Picciano, 2012).

According to Graham, Woodfield, & Harrison (2013), blended learning environments, institutional costs, and evaluative research are challenging due to a lack of consistent variables among course offerings. New and different textbooks, rotating faculty, and changing course assignments and exams create obstacles to researching one class over a period of time (2013). These gaps in blended learning research also have

implications for measuring the efficacy of the CSU implementation strategy to alleviate bottlenecks.

Purpose of the Study

Alleviating bottleneck courses throughout the CSU system is a priority for the CSU Chancellor's Office and the Board of Trustees, and blended learning is actively being explored and implemented as a possible solution to the problems caused by bottlenecks. This mixed method study addressed the outcomes of a CSU bottleneck course that employs blended learning to alleviate the slowing caused by a student demand that outweighs faculty and facility capacities. Specifically, the study focused upon the blended learning environment, student attrition, overall course performance, and the lived experiences of the students in one blended learning psychology course at San Diego State University.

The purpose of this study was fourfold. First, the study measured whether student demographics including race/ethnicity, age, gender, and socioeconomic status explain differences among student attrition and persistence in the blended learning psychology course. If one solution to alleviate bottleneck courses at SDSU is to offer blended learning courses, it would stand to reason that course retention and successful course completion accompany the effort that ultimately aims to secure a timely graduation for students.

Second, the study observed how student demographics explain course performance among the students who remained in the psychology course. Explain, defined as one variable influencing another, thus explaining an outcome in the study; the underlying social causes of student performance are introduced in the qualitative portion

of the study but they are not generalizable. Specifically, student data of those who successfully completed the psychology course with a grade of C or above are compared to the characteristics of those students who received a repeatable grade of a C- or below. In other words, are there relationships between student demographics and students who pass the psychology course, and students who receive a repeatable grade? This piece of the study traces back to the bottleneck issue as it begins to investigate whether or not student readiness and curricular bottlenecks impact specific groups of students.

The third purpose for this study was to understand the extent that student demographics of those who pass the psychology course help explain variations in those students' final course grades. Just as the first purpose of the study focused upon the students who remained in and those who dropped the psychology course, and the second purpose delineated between students who successfully passed the course and those students who received a repeatable grade, the third purpose of the study was designed to generate more information about the demographic relationships between students who successfully completed the psychology course, further depicting the student groups by individual grade assignment.

The fourth and final purpose of this study was to connect the first three pieces with a narrative that illuminated students' opinions of the psychology course, to learn about the experiences of students whose demographic data most significantly explained their overall course performance, and to determine whether the quantitative data outcomes were upheld or unsupported by individual students' experiences in the course. These reasons for individual student performance in the course created a deeper context

for blended learning bottleneck course outcomes. The following four research questions guided this study:

1. To what extent can student demographics explain variation in the course withdrawal behavior of students enrolled in a blended learning undergraduate psychology course at San Diego State University? Specifically, can student demographics explain variation among those students who completed the course and those who dropped the course?

2. Among those students who completed this undergraduate psychology course, to what extent can student demographics and internal course performance data explain variation in those students who received a passing (non-repeatable)[1] grade versus students who received a repeatable grade (C- or lower)?

3. Among those who received a passing grade in the course, to what extent can student demographics and internal course performance data explain variation in the final grades of students in the course?

4. What are the experiences of students whose demographic data most significantly explains those students performance in this blended learning psychology course?

Significance of the Study

This study is significant in a number of ways, but there are three predominant factors. First the study measures learner outcomes in a large-scale California State University blended learning environment. Measuring the predictive relationships between student demographics and course performance will contribute to the dearth of

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[1] San Diego State University defines non-repeatable grades as an A, B, or C final course grade (2015c).

literature in the blended learning sphere, and it will provide San Diego State University and the CSU Chancellor's Office a closer look at the big data in a blended learning course, including independent demographic variables which are not generally analyzed with test outcomes and student attendance (R. Williams, personal communication, 2014).

Second, the study provides evidence of early course intervention windows that may support student success in future classes. Using these predictive data while the course is underway could potentially create opportunities for students to avoid unproductive behaviors that may endanger their chance of passing the highly repeatable class. This research will serve to inform some early quasi-experimental research on student interventions that has already begun.

Third and finally, this study uses quantitative and qualitative methods, coupled with policy analysis and institution-specific informational interviews and data analysis. The big data used in the study originated from different areas on campus and were combined for analysis, but are not generally merged to measure student performance. This research design provides a rich analysis and includes key details of student behaviors and perceptions that would have gone unnoticed in a purely quantitative or qualitative design.

This sequential explanatory contribution offers a different framework to measure the outcomes of blended learning courses and is responsive to Picciano's (2012) Learning Analytics Flow Model and his recommendation that transactions between students and faculty are not sufficient informant measures for courses of action. "The instructional transactions should also be integrated with other resources such as data from the college information systems (student, course, faculty) and an analytics software program. The

logic/decision trees for the latter are based on patterns as well as faculty and advisor experiences, intuition and insights that are used to develop guidelines and rules for subsequent courses of action" (p. 14).
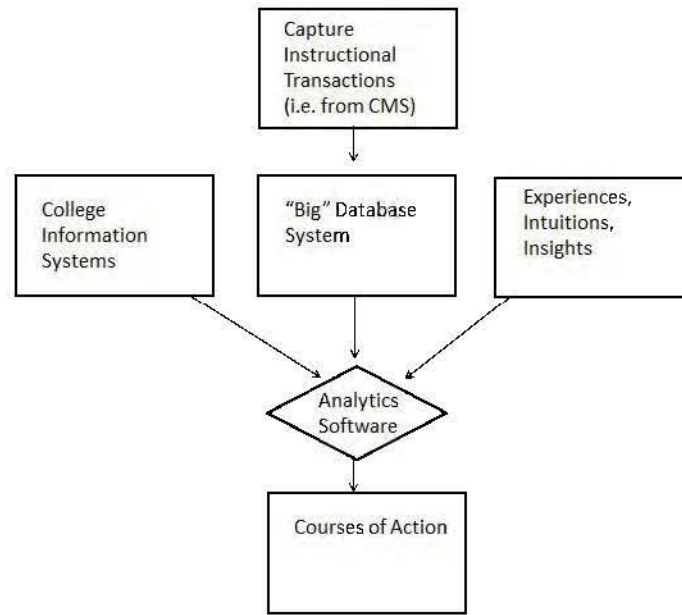
Figure 1. This figure illustrates Picciano's Learning Analytics Flow Model with data from student course performance outcomes, demographics, and lived experiences comprising the analytics, which are then designed for student interventions (2012).

The next chapter provides a review of the literature that informed the problem statement and research design for this study.

CHAPTER TWO

REVIEW OF THE LITERATURE

Overview

California's publically funded higher education system is under tremendous pressure to serve growing student demand with a shrinking budget. Blended learning is one solution being explored by the CSU Chancellor's Office, Board of Trustees and individual CSU campuses as a possible way to serve more students with fewer resources and increased course-related performance data. Two primary spheres of literature, one reviewing California's publically funded higher education system and CSU policies, and the other introducing blended learning and learning analytics. Together these inform the research questions and foundations for the study; each creates a clear and timely space for the research.

The first literature sphere includes some history from the Master Plan for Higher Education in California, specifically the California State University system, its mission and purpose, and the rapid maturation of both the CSU system and the San Diego State University campus. An explanation of germane CSU economics, policies, and the specifics of San Diego State University's impact upon the state will follow. Finally, a thorough explanation of the CSU course bottleneck problem will illustrate how SDSU faces a pressing demand to manage increased student populations with limited resources and how they have responded through blended learning pedagogy.

The second area of literature will review the origins of blended learning pedagogy; specifically, how blended learning varies from face-to-face instruction and early applications of the method. There is little theory relating to blended learning, but

two of the often-cited models and some empirical studies will be reviewed to shape how practice and research are presented in the field.

Gaps in the blended learning literature center on the costs of blended learning, work within the blended learning environment and long-term analyses of blended learning courses. The field of learning analytics, which originally began in the business sector to track market behavior, now complements blended learning. In fact, as higher education's use of digital learning management platforms has increased, the importance of now-available analytic information has increased significantly for individual students and institutions. While the literature addresses the presence of blended learning and learning analytics within the CSU system, it does not explicitly denote how CSU students perform in a blended learning bottleneck course over time.

Public Higher Education in the State of California

The California State University system is part of a larger system within the state. Edmund G. "Pat" Brown signed the Master Plan for Higher Education in California, also known as the Donahoe Act and Senate Bill 33, into law on April 26, 1960. In an effort to unite California's colleges and universities, the act forecasted a system both united and tiered to ensure that citizens could seek an educational opportunity that was accessible and affordable (UCOP, 2014). The system was organized into three segments through the Master Plan, but viewed as an educational continuum.

California's Community Colleges (CCC) were designated to instruct students working toward general education requirements and pursuing vocational education. The two-year community colleges admit students who possess a high school diploma or

equivalent and individuals who demonstrate a capacity to benefit from instruction (CCC Apply, 2012).

California's State University system (CSU) was designed as the institution for undergraduate and master's education. In 2006 Senate Bill 724 allowed students to be awarded the Doctor of Education in educational leadership (California State Legislature, 2005). In contrast, Doctor of Philosophy degrees may be awarded only when the CSU campus works jointly with a UC or independent campus (2005). For example, California State University, Long Beach with The Claremont Graduate University currently offers a Ph.D. in Engineering and Industrial Applied Mathematics (California State University, Long Beach, 2014). Finally, the University of California system (UC) was designed as a research institution for the state and was the only institution originally granted the authority to administer doctoral degrees (UCOP, 2014).

Economic Impact of the California State University System and SDSU

The CSU system has a tremendous economic impact upon California and the United States. To date, there are 3 million alumni, 460,000 current students, and one out of 20 Americans earned their college degree from a California State University campus (Office of Public Affairs, 2015). The system's economic impact within California is responsible for $4.9 billion in annual tax revenue locally and statewide, and a return of $5.43 in CSU-related expenditures for each one-dollar of state investment. In 2008-09 undergraduate and graduate CSU alumni working in California earned an estimated $122 billion in annual salaries (Office of Public Affairs, 2012).

Although the totality of alumni earnings cannot be attributed solely to a CSU degree, the enhanced earning power that degree completion has upon the state economy

is estimated to be $42 billion. When the enhanced earnings of CSU alumni are factored into total economic impact, the direct and indirect return ratio is one-dollar to $23. Taken together, the annual total direct and indirect spending impact of the CSU within California is $70.4 billion with economic activity supporting approximately 485,000 jobs (Office of Public Affairs, 2012; ICF International, 2010).

The increased value of a college degree, coupled with a prolonged economic downturn sent many people back to school. The full-time student, who once represented the traditional student majority, is now among an increasing number of non-traditional students (Ross-Gordon, 2011). These students may commute to school, maintain nighttime class schedules, hold full-time jobs, and possess veteran status. Regardless, both student groups are subject to increased demand for classes with shrinking state budgets and finite classroom availability.

In 2010-11 CSU enrollment increased from 328,190 full-time equivalent students (FTES) to 341,250 with the CSU state allocation moving in the opposite direction, from $2.79 billion down to $2.06 billion (California State University, 2012). The CSU system tries to keep the student's share of costs down with tuition between $6,000 and $7,000 per year (The California State University, 2015). However, a new student success fee will add to the overall cost of attendance. This fee varies from campus to campus and fee implementation at San Diego State began at $100, rising to a maximum of $512 in 2018-19. The fees are designed to hire tenure-track faculty, and to ultimately help students graduate on schedule (San Diego State University, 2015a).

When students' time to degree completion increases, the slowing is termed a bottleneck. Alongside the slowing, costs also increase for the student and the institution

(California State University Board of Trustees, 2013; The California State University Office of the Chancellor, 2013). Although the administrative costs attributable to bottlenecks are not well articulated in the literature, the extra work is felt by students, faculty and administration campus wide.

For example, the university registrar is responsible for transactional course adds, drops, and the processes associated with students repeating classes (San Diego State University, 2015b). In addition, the institution incurs labor, departmental resource, facility use and maintenance costs. Similarly, students bear costs associated with tuition, student fees, and ongoing ancillary charges including housing, textbooks and meals. Taken together, all of these costs are exacerbated with bottleneck slowing. Given the significance of the bottleneck problem, the California State University Board of Trustees has identified, classified and prioritized a search for strategies to alleviate four types of bottlenecks (California State University Board of Trustees, 2013; The California State University Office of the Chancellor, 2013).

Bottleneck Courses

Bottleneck occurrences in the CSU system have become a priority for analysis and alleviation. In 2013 the CSU Chancellor's Office began working to identify and define the causes of bottlenecks from an individual campus and system perspective.

Student readiness and curricular bottlenecks. The first type, student readiness and curricular bottlenecks, occur when a student is not academically prepared to take a particular course and ultimately receives a repeatable grade. This bottleneck classification affects students attempting first-time class registration and those retaking courses after receiving a repeatable grade. The term "repeatable grade" refers to any

grade assignment below a C at CSU campuses that employ a plus/minus grading system (San Diego State University, 2015c). For CSU campuses that do not utilize the plus/minus grade scale, an assignment of a D or lower qualifies as a repeatable grade (California State University, Long Beach, 2013).

In order for CSU students to remain in good standing, they are required to maintain a minimum grade point average of 2.0 in both general undergraduate study and within their major program (San Diego State University, 2015c). When a student receives a repeatable grade they have the option to repeat the course once in an attempt to receive a higher grade via the Course Forgiveness allowance (2015c). The second option for students who receive a repeatable grade is to leave it on their transcript. Students who receive an F in a class do not receive college credit for that course. Students who receive a D are adding grade points to their transcript that register below the university requirement of a 2.0 or C grade point average. Students repeating courses each semester, when combined with those taking classes for the first time, increases overall course demand (Smith & Hanley, 2013). Although student performance outcomes create one type of bottleneck, there are additional factors that affect different CSU campuses including the size and scope of course offerings.

Place-bound bottlenecks. Place-bound bottlenecks occur when students are required to wait for the availability of specific course offerings. Place-bound bottlenecks occur more frequently at smaller CSU campuses with multiple programs but fewer resources than larger campuses (Smith & Hanley, 2013). For example, a biology department may offer a required upper-division course once a year during the fall semester; if a student in the student's final year of study is unable to secure a place within

the course that student may not be able to finish his or her studies until the following fall semester. While place-bound bottlenecks occur at smaller institutions, campuses large and small often reach maximum capacity, creating facilities bottlenecks.

Facilities bottlenecks. Classroom space limitations and scheduling challenges often prevent the addition of sections to satisfy student demand for course sections. Space limitations connect to the third classification under the CSU bottleneck umbrella, facilities bottlenecks. Frequently occurring in science, technology, engineering and mathematics (STEM) courses, facilities bottlenecks are caused when classes require spaces designated to serve a specific discipline or sizable class population. Once available lecture halls or campus laboratories are scheduled, no additional sections can be added to course offerings (Smith & Hanley, 2013).

Advising and scheduling bottlenecks. Not all bottlenecks arise from space or resource limitations. Academic planning also plays a role. Advising and scheduling bottlenecks occur when students, "do not receive the most timely and informative advice about their academic pathways and course schedules" (Smith & Hanley, 2013, p. 1). When students are unaware of academic scheduling efficiencies or course enrollment opportunities, it slows their timely progress toward degree completion. Technology, however, now enables opportunities for alerting students of course openings and strategic academic pathways based upon their major, grades, and time to graduation (2013).

Identification of bottleneck types hopefully represents the beginning of the resolution process. In the summer of 2013 department chairs at CSU campuses received a survey asking for information regarding bottleneck courses. The results of the survey confirmed that bottlenecks were prevalent throughout the system and that plans for

blended learning interventions were already underway at the campus level (Vogel, 2013). Additional initiatives poise the state for a digital future in higher education.

Pending California Higher Education Online Policy and Funding

Funding and political action are both at work to alleviate bottleneck courses and move California's higher education system toward lower costs and greater efficiency through the use of technology. Governor Jerry Brown recently allocated $16.9 million to the California Community Colleges in order to boost the use of technology on campus. The courses with the highest demand will be those with the highest priority to receive technological support measures and developments (State of California, 2013). Similarly the Governor committed $10 million for California State Universities to alleviate bottlenecks and to get California undergraduate students through to graduation (2013).

One project specifically targeted to alleviate bottlenecks on CSU campuses is Proven Course Redesign, which incentivizes faculty to incorporate technology in their courses to increase student success. Examples include blended learning and virtual labs. Faculty who participate in the program receive training and best practices examples to guide their work. However, the program, now in its third year, has not proven to increase student success or to decrease bottlenecks on campus (Course Redesign with Technology, 2013).

Senate Bills 1052 and 1053 also work to help alleviate the strain on California's public institutions through a proposed decrease in student textbook spending. The two enacted bills (SB 1052 and 1053) propose analysis and implementation of digital textbooks and open source networks for students to virtually "borrow" content while they take their courses (State of California, 2013a). Once selected, students will be able to

borrow required textbooks for core courses at low or no cost. Licenses and copyrights would reside within the construct of what will be a digital library (State of California, 2013b). Both bills made their way through the legislature and were signed into law in 2012. As the California Legislature, CSU Chancellor's Office and the CSU Board of Trustees make online learning a priority, so do the individual CSU campuses.

Blended learning and MOOCs. Blended learning and massive open online courses (MOOCs) were recently unknown terms, and now they appear in the headlines of *The Chronicle of Higher Education*, as well as in scholarly journals and nationwide publications. In the eyes of California's state higher education systems, blended learning courses and MOOCs offer structures that move away from the constraints that contribute to the current bottlenecks, including time, space, and student cost (Hattori, 2013). It should be noted, however, that there are distinct differences between MOOCs and blended learning. For example, MOOCs are courses taught entirely online, often to *any* person who desires to participate in a course. Since there are generally no limits to course enrollment, groups ranging from 20 students to hundreds of thousands can matriculate at one time (EDUCAUSE, 2014). Courses can be taken for credit in some instances, or students engage in them for the experience and content knowledge.

Currently, the CSU and California Community Colleges are investigating and implementing MOOCs as an experimental option to alleviate bottlenecks. San Jose State University (SJSU), for instance, experimented with MOOCs in 2013, by offering psychology, statistics, and introduction to programming courses. Students paid the same tuition as with other courses; however, the courses were also available free of charge to the public, although not for official credit. Instead, public participants had the option to

complete the courses for a certificate, rather than college credit. The experiment, however, was paused and ultimately redesigned as an Extended Studies program due to extraordinarily low pass rates among SJSU students (Straumsheim, 2013; San Jose State University, 2014).

In 2006 SDSU Professor Mark Laumakis began implementing a blended learning model in his introductory psychology class (Psychology 101) at San Diego State University; in 2009 the impetus for a blended learning pedagogy became budget-driven per the institution. Given the importance of Laumakis' work and the fact that this research involves an empirical study of this very class over 16 semesters, the next section provides an in-depth look at a Sloan Consortium evaluation of the blended learning class.

SDSU case study and the Five Pillars: Sloan-C Quality Framework. Mark Laumakis is a lecturer in the Department of Psychology at San Diego State University (SDSU) and he also holds a Faculty in Residence role within Instructional Technology Services at the same institution. Laumakis has been teaching Introductory Psychology employing blended learning pedagogy since Fall of 2006 (Laumakis, Graham, & Dziuban, 2009), and his two blended learning course sections each have a roster of about 500 students every semester. Although there are not many instruments or theories in blended learning, Laumakis wanted to ensure that his students were taking the course within a quality educational environment. Laumakis used the Sloan Pillars to redesign the course in a blended learning environment with features to enhance the learning experience (Laumakis, Graham, & Dziuban, 2009).

Sloan Consortium. The Sloan Consortium is an online learning society whose primary purpose is the study and evaluation of online learning (Sloan-C, 2013). The

Sloan-C Quality Scorecard for Online Programs (QSC) began as an evaluative instrument for online asynchronous learning but researchers found that it also applies to the assessment of blended learning environments (Laumakis, Graham, & Dziuban, 2009). The instrument measures 74 quality indicators that inform overall blended learning course performance categories, also known as The Sloan-C Quality Framework, which can be found in its entirety in Appendix B (2013). The framework is divided into five categories, or pillars including: learning effectiveness, cost effectiveness and commitment, access, faculty satisfaction and student satisfaction (Moore, 2005).

Each of the Sloan-C Pillars is described with a goal, process or practice, sample metric, and progress indices for ongoing measurement. In the case of SDSU, Laumakis began teaching the introductory Psychology 101 class in 2004 and focused upon improving the Learning Effectiveness (LE) of the course by adding blended learning enhancements (Laumakis, Graham, & Dziuban, 2009). Unintended outcomes of the course changes were improvements to both Access (A) and Student Satisfaction (SS) within the new learning environment. This means that students were able to learn while located off-campus and through the use of mobile devices. In addition to being able to access the material, students were pleased with the content and learning experience (2009).

Course changes. Changes to the course included redesigning the in-class experience and moving 45 percent of the formerly face-to-face content into a synchronous, remote learning environment. Course activities included 10-20 minute mini-lectures and demonstrations (Laumakis, Graham, & Dziuban, 2009). Synchronous learning required students to be present, while the live lecture was in session. The online

course sessions were recorded and available to students after they were conducted but attendance was calculated only based upon live student presence. The study shows about 150 of the 500 students attended the synchronous online sessions, which were delivered via Wimba Live Conferencing, a web conferencing tool that resides on SDSU's Blackboard Learning Management System (Laumakis, Graham, & Dziuban, 2009).

Clickers. The psychology course was also redesigned to increase student engagement when the class met live in a face-to-face setting. The employment of clickers, or personal student response systems, in the classroom aided in the course enhancements (Woelk, 2008). A "clicker" is a simple remote device that is used on-site and generally has multiple-choice buttons. Sometimes a clicker will have additional features including a delete or send button. Faculty, including Laumakis, employ clickers in the classroom to poll participants and the results are tabulated and rendered instantaneously. Students generally own a clicker, they are sold at campus bookstores, and sometimes institutions will loan the devices to students.

In the course redesign Laumakis used clickers to measure student participation and employed the devices as a strategy to engage students on a personal level within the large lecture environment (Woelk, 2008). The question prompts that required a clicker response were designed to check on student content comprehension during live demonstrations and for students to understand psychology concepts based upon questions and responses from the class population. A technique called Peer Instruction was also used in the course (Mazur, 1996).

Mazur's approach poses a question to the class where members are asked to collaborate in small groups and state their rationale for the correct answer (1996). In

Laumakis' class, participants submit their individual responses via clicker, and their collective responses are displayed on the course screen, but the correct answer is not revealed to the class until students collaborate and resubmit an answer. The correct answer is then revealed to the class (Laumakis, Graham, & Dziuban, 2009).

Course assessments. The course redesign efforts were derived from the Sloan-C Pillars and the same model was used to evaluate the outcomes of the new course design. Laumakis assessed the SDSU blended course redesign six different ways. A mid-semester check-in survey was distributed via email through Survey Monkey, an easy to use online assessment platform. Educational Technology graduate students conducted in-class observations, and the Students Ratings of Instruction assessment instrument from the Individual Development Education Assessment Center (IDEA) was administered. Students were included in post-course focus groups, in addition to regularly administered course evaluations and grade analysis conducted after each semester. Six evaluative measures have since been packaged as the SDSU Evaluation Toolkit (Laumakis, Graham, & Dziuban, 2009).

Face-to-face course and blended learning assessment outcomes from Fall 2006 through Spring 2008 yielded some surprising results. Blended learning tracked slightly behind the face-to-face course evaluation scores during the first semester, but recovered quickly and pulled ahead of the traditional counterpart in short time. The Sloan-C Pillars of Learning Effectiveness (LE) and Student Satisfaction (SS) were impacted by the learning environment changes made in the classroom with an uptick in teacher evaluation and overall progress of course objectives. These increased score comparisons were not only higher than the comparable face-to-face course scores, but also the thousands of

courses in the Individual Development Education Assessment Center database

(Laumakis, Graham, & Dziuban, 2009). The case study at San Diego State is one

example of the work that is being done within the CSU system, to deliver and improve

upon blended learning methods in classrooms.

Blended Learning

Blended learning is defined as the combination of "face-to-face instruction with

computer-mediated instruction" (Bonk & Graham, 2006, p. 5). However, blended

learning is not as straightforward as it may sound. Described as the "ongoing

convergence of two archetypal learning environments" (2006, p. 5), blended learning

embodies the pedagogical traditions of the brick and mortar institution, while

simultaneously incorporating emergent digital technologies.

Only recently have consumers of self-paced continuing education and instructor-

led learning through traditional classroom courses engaged in the same learning space at

the same time. Now, with the availability of portable, wireless technologies and an

emerging blended learning platform, students who were previously unable to attend

traditional classroom lectures are part of the higher education learning community.

Today's learner is able to access education regardless of professional or family

commitments because of the malleable learning schedule for many of the courses offered

in a blended learning format (Dziuban, Moskal, & Hartman, 2005).

Where did blended learning originate? Blended learning began with the

distributed learning environment, also known as distance learning (Daniel, 1997). One

way to examine the spaces where blended learning occurs is through the differences

between face-to-face and distributed learning environments, illustrated in Figure 2. The

four dimensions of learning interaction outlined by Bonk and Graham (2006) each appear

as a continuum and include: space, time, fidelity, and humanness. Understanding these

dimensions helps with navigating language that appears in the blended learning literature.
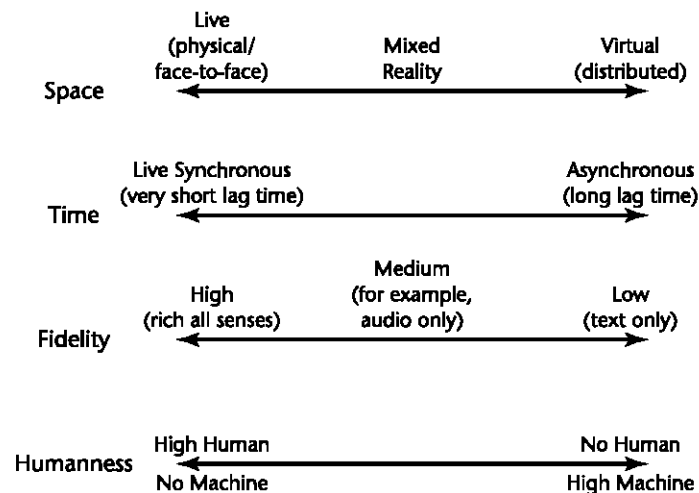
Figure 2. This figure illustrates the Bonk and Graham continuum of the four dimensions
of interaction in face-to-face and distributed learning environments (2006).

Space. Space is described as one of the four dimensions that define interactions

in face-to-face and blended learning environments, and according to Bonk and Graham

(2006), is the physical distance between the learners and where the instruction takes

place. When courses are taught in a face-to-face environment this space is described as

"live" and "physical", since the learner is in the classroom where instruction is taking

place. This live environment resides at the far left side of the continuum in Figure 2.

Courses taught in an entirely virtual environment are defined as distributed

learning, and reside at the other end of the continuum. These include online courses or

those viewed as recordings at an off-site venue. For example, a university may have a

remote campus, offering courses in a specific major. California State University, San

Bernardino (CSUSB) offers undergraduate, certificate, credential, and graduate programs

via interactive, closed-circuit television and online instruction between San Bernardino
and Palm Desert, California – a city about 70 miles east of the CSUSB campus (CSUSB,
2013).

The term "mixed reality" appears at the midpoint of the continuum describing
space in a blended learning environment. Mixed reality is comprised of live and virtual
learning environments. For example, Dr. Laumakis' class meets on Tuesdays and
Thursdays, but the Tuesday lectures are viewed online and the Thursday lectures are
presented live in the classroom. Students may be offered the opportunity to view the
Tuesday online lecture during the designated class time, or they can opt to view a
recorded version any time before class reconvenes on Thursday. Time is where blended
learning becomes increasingly flexible for students.

Time. Much of the blended learning discussion centers on time. The terms
"synchronous" and "asynchronous" learning are polar opposites. Synchronous learning
occurs when the participants are in the same place at the same time (iNACOL, 2011).
Classroom lectures and live course videos or closed-circuit television feeds are examples
of synchronous learning environments. In contrast, asynchronous learning occurs when
time separates communication exchanges between participants. Online discussion
threads, email, or recorded video lectures are examples of asynchronous learning
environments (2011).

Synchronous learning and other blended learning terminology were defined by a
working group of professionals as a part of the *Online Learning Definitions Project*
(iNACOL, 2011). The International Association for K-12 Online Learning (iNACOL)
project is a K-12 initiative, but the synchronous and asynchronous definitions also apply

to the context of this research. Scholarly work dedicated toward defining blended

learning varies among researchers, and some researchers have expanded and refined the

definitions over time. In 2011 iNACOL published the *Online Learning Definitions*

Project with the intent to create a shared understanding of blended and online learning

initiatives, practices, and policies. This work represents a start to the shared

interpretation of blended learning, but variations on the theme continue.

Some definitions of blended learning in higher education, however, impact "seat

time" which is not subject to the same regulations as K-12 education. Blended learning

may include a purposeful reduction of in-class time in varying percentages (Garrison &

Vaughan, 2008). Research has yet to indicate an ideal formula, if one exists at all, for in-

class and distributed learning time. Of course, time in and out of class within blended

learning environments varies based upon courses and lessons. It is through the reduction

of seat time where synchronous and asynchronous learning environments come together

in a blended learning space.

For example, the students who attend class online via pre-recorded class video on

Tuesday and on-campus on Thursday are spending 50 percent of their class time in a

synchronous learning environment and 50 percent in an asynchronous environment.

Students, however, who attend both classes when they are scheduled in the classroom and

via live streaming video online, are attending 100 percent of the class in a synchronous

learning environment. Both are examples of blended learning class scenarios.

Fidelity. Depending upon how a course is conducted, the next element, fidelity,

is measured by the enrichment of the body's five physical senses. In the past, face-to-

face instruction was the only way to access all of the senses, leaving only sight and sound

available to distributed or asynchronous learning environments. As technology develops, touch, sight, and sound can all be accessed from remote locations, leaving only taste and smell within the realm of the face-to-face classroom experience. For example, students studying anatomy may use a touch screen iPad equipped with an application that requires them to touch different areas of a diagram, identifying components and functions of the human heart.

High fidelity learning environments remain on the face-to-face instruction side of the scale, where students can potentially experience the lesson through all five of the senses. On the other side of the spectrum, an example of a low fidelity learning environment is reading a textbook. An example of a medium fidelity learning environment as described by Bonk and Graham (2006) involves having access to audio. Many courses now employ technology and methods to heighten the senses in a high fidelity learning environment. These advancements are possible through the development and speed of technology delivery, innovative lesson planning, and learning management systems (LMS).

Learning management systems can be thought of as online spaces used to organize course materials and can be used to support face-to-face, distributed, or blended instruction. The online platform generally requires a login authorization to access a specific course where readings, videos, discussion groups, and private messaging options are available to course participants. Blackboard is one example of a learning management system utilized by thousands of institutions including those within the CSU system. Importantly, implementation of digital resources in classrooms has significantly

reduced the gap between high and low fidelity as well as the differences between distributed and face-to-face learning environments (Bonk, & Graham, 2006).

Humanness. The fourth and final dimension that differentiates distributed and face-to-face learning environments is humanness. When participants are in a learning environment together, the environment is labeled "high human." When participants are not in the same space and are instead using computers, televisions, and online tools to facilitate the learning process the environment is labeled "no human" or "high machine" (Bonk, & Graham, 2006). An example of high human interaction would be students working on a dissection exercise together in a classroom. The same work could be simulated in the online touch screen iPad biology application mentioned earlier. Students would log onto the application remotely and without an actual dissection subject, instead practice on a digital representation of a human heart. The simulated work represents zero physical, human interaction, but still holds instructional value as students learn the different areas of the heart as a group.

Research and blended learning. As face-to-face and distributed learning environments amalgamate to create blended learning, thousands of corporate training divisions, K-12 schools, and higher education institutions are employing some variation of the instructional method within the classroom. Where exactly blended learning occurs is difficult to track because of the ongoing development of definitions and implementation methods. However, the National Center for Education Statistics (NCES) continues to work towards measuring blended learning in American universities.

The NCES report on Distance Learning at Degree-Granting Postsecondary Institutions: 2006-07 represents the fourth survey of distance learning since 1995, but

contains very little comparable data from the previous three reports because blended

learning definitions and criteria have changed significantly (Parsad, & Lewis, 2008). The

National Center for Education Statistics data show 65 percent of 2-year and 4-year Title

IV degree-granting institutions offered for-credit courses in a distance education format.

The data also show that of the 12.2 million registrations in the 2006-07 school year, 12

percent or 1.46 million of the course participants were engaged in blended courses

(2008). Although the NCES has not released a new report, it can be assumed that the

number of students receiving distance education have grown exponentially since 2006.

Review of NCES data from 2006-07 affirms the assertion of researchers that there

are considerable gaps in blended learning research. Existing studies reveal little

empirical research, and fewer studies still, focus upon the theoretical and cost benefit

analyses within blended education (Halverson, Graham, Spring, & Drysdale, 2012).

These research gaps occur when blended learning criteria and individualized institutional

approaches are changed. As a result, assessment measures and longitudinal data are

impacted by the changes; making blended learning a difficult field to measure.

One study however, is focused upon cataloging existing research available on the

topic of blended learning. The study tracked the number of doctoral dissertations and

master's theses written about blended learning. The same researchers, Halverson et al.,

(2012) published an article identifying the most frequently cited blended learning

research literature. In this study, 50 articles, 25 book chapters, 10 books, and 15 non-

academic publications were identified. Dissertations and theses were not included in the

first study, but the post-secondary student research were analyzed and organized

separately to paint a clearer picture of blended learning literature, in a companion piece to the original research.

Data from the research trend study showed a steady increase in theses and dissertations on the topic of blended learning have been published since 2001 (Drysdale, Graham, Spring, & Halverson, 2013). Ultimately 205 manuscripts fit within the search term parameters of blended learning. These included papers investigating methods, instruction, and similar terminologies connecting dedicated research to the topic of blended learning. The findings show a gradual increase between 1999 and 2005, followed by a sharp spike of 15 additional manuscripts between 2005 and 2006. Another significant publishing spike occurred moving from 29 manuscripts in 2009, to 44 in 2010 (2013). Among the research areas, topical trends were identified as learner outcomes, dispositions, instructional design, interaction, and comparison.

Learner outcomes. Blended learning outcomes were addressed in more than half of the research manuscripts (Drysdale, Graham, Spring, & Halverson, 2013). Grade point averages, test performance, and retention were among the topics evaluated. In one study of blended learning methods in a community college environment, the researcher found that the results were similar to those found in two studies conducted at the University of Wisconsin, Milwaukee and the University of Central Florida; specifically, the researcher found that students who studied in a community college blended learning environment reported higher course satisfaction than those in comparable face-to-face classes. Blended learning students also outperformed students in grades and retention than those students enrolled in similar face-to-face courses (Hackemann, 2010). These three accounts, however, did not include enough participants or variables to validate

blended learning as having greater efficacy than a face-to-face learning environment, but the research does indicate that further studies may reveal more about learner outcomes (2010).

Dispositions. One third of the manuscripts analyzed included what the researchers coded as a "dispositions" theme. This theme means that researchers in the field were studying how students in blended learning environments felt about their work, the workload, and how to manage online and face-to-face encounters. The disposition code included research that addressed perceptions, attitudes, expectations, and learning styles of blended learning students. Perception was the most discussed sub-topic under the disposition code because it measured both student and instructor feelings towards blended learning. These could be positive or negative considerations, but researchers found that many students had positive dispositions towards blended learning environments, among them, convenience and fast feedback loops (Drysdale, Graham, Spring, & Halverson, 2013).

Instructional design. As the field of blended learning quickly develops, researchers are working to measure and understand how best practices can be employed to construct blended learning courses. Blended learning is considered to be a practice where the instructional design requires "innovation beyond the expertise of the traditional instructors" (Drysdale, Graham, Spring, & Halverson, 2013, p. 96). Some of the studies include best practices for instruction, while others investigate the concepts surrounding an ideal blend of face-to-face and online instruction. A research gap in the areas of evaluation and environment was identified through the analysis (2013). Evaluation and blended learning environments are difficult to study because the classroom variables

often change. For example, a professor who adopts a new textbook or adds additional exams in-class and online, could change the blended learning environment.

Interaction. Interaction is defined as the various relationships between students and instructors, students and other students, students and the educational content, and students, instructors and parents (Drysdale, Graham, Spring, & Halverson, 2013). Although the research did not indicate whether there is a specific area where studies tend to center, a gap was identified among interactions that did not appear in the studies. For example, theses and doctoral dissertations focused upon the people involved in blended learning and on learner-instructor relationships, but the literature did not show studies including learner-content interactions (2013).

Without a critical analysis of how learners and instructors interact with the content through face-to-face or distance learning, educational outcomes cannot be measured. Educational content is being discussed in other areas, however, as there is considerable discussion regarding copyright permissions and direct contact between learners and content providers, so this is indeed an important topic from the student, research, and practitioner perspectives (Plank, 2013).

Comparison. One of the biggest questions regarding blended learning is whether it is as effective, more effective, or less effective than traditional face-to-face education. Studies that employ two or more instructional methods, classroom environments, or student characteristics, comprise some of the comparison research that has been conducted within the blended learning field. None of these themes show strong outcomes in terms of cross-study comparisons. The meta-analytic research does indicate that

blended learning is favored over other learning approaches, but why this is the case is inconclusive (Drysdale, Graham, Spring, & Halverson, 2013).

   Minor Trends. Among the smaller research topics included in the manuscripts, it is noted that student demographics were studied more often than the demographics of blended learning faculty. In addition, according to researchers, technology was not discussed in proportion to the impact that technological infrastructures have upon blended learning operations. Researchers posit that this gap may be attributed to blended learning scholars relying upon existing distance education literature to answer the technological research questions (Drysdale, Graham, Spring, & Halverson, 2013).

   Meta-analysis of blended learning research is important because the field is young and developing trends are still coming together. Studies outline areas that are ready for researchers to investigate; these include learner-content interactions and how technology is used in blended learning environments. Other areas require the development of reliable and valid instruments before comparing traditional classroom education to that of a blended learning course. Between the development of the discipline and the study of how it is implemented in the classroom, there is plenty of analytic work still to be done on the general underpinnings of blended learning.

   Pedagogical modeling in blended education. Researchers and educators have compiled an extensive body of classroom and online teaching approaches within a comparatively short period of time. Similar to the meta-analysis on blended learning research trends, gaps within these works are highlighted, pointing to a need for more information surrounding both theoretical foundations and modeling for blended education. Without a theoretical foundation specifically designed for blended learning,

methods will continue to be based upon distance education and variations upon classroom instruction themes.

In an attempt to understand blended learning from a theoretical perspective, researchers have been borrowing frameworks from the field of distance education, including transactional distance and industrialized education theory (Drysdale, Graham, Spring, & Halverson, 2013). One theoretical framework that has been adapted specifically to serve blended learning research, is the Community of Inquiry (CoI). The framework by Garrison and fellow researchers was originally created in 2000 for text-based online learning research and practice (Garrison & Vaughan, 2008).

Community of Inquiry. There are two primary texts available within blended learning research. The Handbook of Blended Learning: Global Perspectives, Local Designs (Bonk & Graham, 2006) is by far the most noted text with more than 470 publication citations (Halverson, Graham, Spring, & Drysdale, 2012). Second to the Bonk and Graham text is the often cited, Blended Learning in Higher Education: Framework, Principles, and Guidelines (Garrison & Vaughan, 2008). Neither of these is the definitive text on blended learning, but both books take the research beyond the stand-alone journal article and move into the field of practice. Blended Learning in Higher Education focuses upon grounding blended learning in the Community of Inquiry (CoI) model, pictured in Figure 3 below.
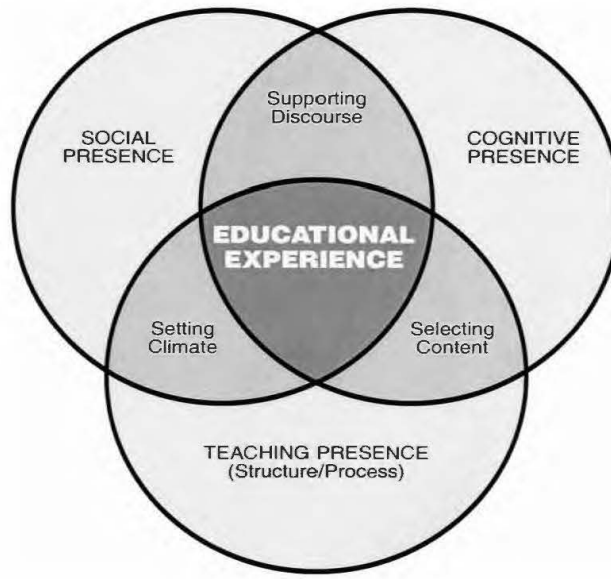
Figure 3. This figure illustrates the Garrison and Vaughan Community of Inquiry framework, one of the few distance education/blended theory models.

Although the CoI model was created from data collected through online computer mediated conferences before blended learning emerged, the authors recognized that the framework also worked to support the merger between traditional face-to-face education and online learning (Garrison & Vaughan, 2008). Three elements comprise the CoI model: the cognitive, social, and teaching presence (Garrison, Anderson, & Archer, 2000). The three elements overlap to create additional facets within the CoI model, and ultimately establish the educational experience.

Cognitive presence represents curiosity or a question in search of an answer within CoI. Teaching presence, another one of the three elements within the Venn diagram, represents the facilitation of learning processes. When the two elements overlap, the function of "selecting content" fills the space. For example, curious students combined with learning facilitation yield a search for appropriate content. The straightforward CoI framework keeps theory and practice in the same space, allowing for

innovation in other areas, including content delivery (Garrison & Vaughan, 2008).

"Without order and a means to construct the rationale for adopting a particular technique,

we are condemned to thrash about and to randomly search for what may work with little

understanding of why something was successful or not" (2008, p. 13).

The three elements are important together, while remaining entirely

interdependent with the additional functions in order to complete the CoI framework

(Moller, L., & Huett, J. B. (Eds.), 2012). The authors note that symmetrical overlap

within and between areas is not a prerequisite, as many of the factors will have varying

impact at any one time (Garrison & Vaughan, 2008). Essentially, there are times in the

learning environment when cognitive presence is greater than the social presence. An

example of this disproportionate modeling could occur during finals week when students

are at the end of a course, focused upon their studies, and social needs are less important

than they were at the beginning of the term when students are building networks and

meeting classmates. The definitions of each element below help explain how they work

independently and together in the CoI model.

Social presence. The first element within the CoI model is social presence, which

is the prerequisite for students to be able to communicate openly within the learning

community. Categories in the social presence element include group cohesion and the

importance of camaraderie (Garrison & Vaughan, 2008). In face-to-face education

environments the social presence task has historically been conducted through icebreaker

activities and in-person introductions. In its inception, online education raised concerns

surrounding the absence of verbal and physical cues for students to introduce and define

themselves in the classroom community (2008). This is no longer the case since

technology now allows for augmented means of communication through computers and mobile devices. The incorporation of audio, video, touch screen activities and synchronous lesson plans within the blended learning classroom environment are proving to fulfill the absence of traditional face-to-face social interactions.

Cognitive presence. Inquiry, coupled with a cyclical process moving through experience, reflection, conceptualization, action, and on to more experience, comprises the basic inquiry process. Garrison and Vaughan based this function of the CoI model upon Dewey's inquiry of the scientific process (2008). When the CoI model developed into a blended learning theoretical framework, a later synopsis of the cognitive presence element was described as the, "extent to which learners are able to construct and confirm meaning through sustained reflection and discourse" (Moller & Huett, (Eds.), 2012, p. 192). Question prompts and online community discussion boards are examples of strategic ways to engage students in cognitive presencing in a blended learning environment community (Garrison & Vaughan, 2008; Garrison & Cleveland-Innes, 2005).

Teaching presence. Teaching presence is the element that brings the model together. Instructor leadership, planning, execution, and ongoing facilitation are the elements that foster the learning experience, including both social and cognitive presence. Research indicates that teaching presence is the space where Community of Inquiry thrives or suffers within the blended learning environment (Garrison & Vaughan, 2008). Individual faculty and the learning community need to be present to the demands and maintenance of a blended learning model. Through the model and guidance shared in the Blended Learning in Higher Education text, faculty are encouraged to engage in a

reflective process, to experience the blended learning model as the students would, and to regularly evaluate the learning environment (2008).

Ongoing CoI research. As online and blended learning courses continue to grow, the CoI model remains a resource to analyze online learning communities. The CoI model is described as a "collaborative constructivist model of online learning processes that can inform both research and practice" (Moller & Huett, (Eds.), 2012, p. 98). However, blended learning practice will eventually require models and measures that are designed specifically for the discipline. As more students and faculty work on learning management system platforms within a blended learning context, data will emerge that will eventually shape trends.

The National Survey of Student Engagement (NSSE) is beginning to hone in on the predictors of student success and the role of technology in learning. The large-scale survey measured 31,000 students at 58 institutions and discovered positive correlations between NSSE measures and students who took courses from institutions that employed high-tech communications and course management systems (Moller, L., & Huett, J. B. (Eds.), 2012). The next phase in understanding online and blended learning performance assessments are the emergence of measures to examine the predictive potential, development, and application of the CoI framework (2012).

Blended learning rests upon a thin theoretical foundation with great potential for theoretical and practitioner research, but little information to direct the research itself. Linking the emerging discipline to measurement seems like the next logical step, and it is beginning to happen on a more sophisticated level through the application of learning analytics. Picciano's (2012) work resides in both blended learning and learning analytics

research, creating new and innovative ways to apply learning analytics as a measurement

of blended and online learning.

> Traditional face-to-face instruction can support traditional data-driven decision-making processes, however, to move into the more extensive and especially time-sensitive learning analytics applications, it is important that instructional transactions are collected as they occur. This would be possible in the case of a course management/learning management system (CMS/LMS). Most CMSs provide constant monitoring of student activity whether they are responses, postings on a discussion board, accesses to reading material, completions of a quiz, or some other assessment. (p. 13)

Using the tremendous amount of data that blended learning interactions yield

provides researchers with the opportunity to analyze course student performance en

masse, which in turn leads to the growing trend of learning analytics.

Learning Analytics

While blended learning is an emergent piece within the higher education sphere,

learning analytics follow closely behind measuring both progress and areas for

improvement. Learning analytics has its genesis in the area of business intelligence (BI),

which is the electronic driver for corporate inventories, banking support and fraud

detection, and the prediction of future consumer demands (Chaudhuri, Dayal, &

Narasayya, 2011). When higher education moved toward using learning management

systems to teach, gather assignments, grade students, and to measure student time and

interaction with LMS platforms, the opportunity to employ analytic methods similar to

those in BI became available. Simply stated, learning analytics can track student

performance, academic behaviors, and foster predictive modeling in a way that allows for

earlier interventions for students in academic distress (Buckingham Shum, 2012;

Picciano, 2012). Shum (2012) goes on to explain:

One of the more advanced uses of analytics that generates huge interest is the possibility that from the pattern of learners' static data (e.g., demographics; past attainment) and dynamic data (e.g., pattern of online logins; quantity of discussion posts) one can classify the trajectory that they are on (e.g., "at risk"; "high achiever"; "social learner"), and hence make more timely interventions (e.g., offer extra social and academic support; present more challenging tasks). (p. 5)

Despite interest and demand, research in the area of static and dynamic data analysis for predictive modeling of student success is sparse.

Where did learning analytics originate? The definition of learning analytics for the purpose of this study was first articulated at the inaugural Learning Analytics and Knowledge (LAK) Conference in 2011. "Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising [sic] learning and the environments in which it occurs" (Siemens, 2011, para. 6). This definition evolved from the work of business intelligence, which also uses big data to spot trends in consumer behaviors and create predictions of future behaviors with the support of digital data analyses. Business intelligence, for example, is the engine behind retailors' ability to generate coupons for similar purchase items and custom advertisements that appear in outer margins of consumer webpages after individual web queries.

Learning analytics use data that reside on campus computer servers as a measure of student consumer behavior. Although institutions of higher education collect and store tremendous amounts of data through grade records, admissions, retention and attrition occurrence, budget allocations, financial aid, and fundraising activities, these data are typically compiled in silos and not addressed until the end of the academic year (Long, & Siemens, 2011). Unfortunately, when data are analyzed on an annual basis it is often too

late to address gaps, problems, and possible solutions (Long, & Siemens, 2011; Picciano, 2012). Further, these data silos are rarely combined, and methods to do so are, at present, unwieldy. However, viewing student behavior in the aggregate has multiple benefits, including improvements in administrative decision-making, the real-time identification of at-risk students, and institutional strengths and weaknesses (Long, & Siemens, 2011).

Types of learning analytics. Learning analytics require acute boundaries to remain organized both digitally and logically. Three levels articulate broad categories of analytics; these include macro, meso, and micro-levels (Buckingham Shum, 2012). Each of the levels inform the next, beginning with to systemwide analytics down to granular individual data. Similarly institutional and systemwide trends inform how to make decisions to serve students on an individual basis (2012).

Macro-level analytics. Macro-level analytics are implemented when institutions look at trends across entire systems (Buckingham Shum, 2012). For example, the CSU Chancellor's Office may look at student persistence across the 23 campuses over time using macro-level methods. Macro-level analytics also fall within the category of academic analytics, which are informed by learning analytics. Academic analytics typically have regional, national or international foci and governmental or educational beneficiaries (Long, & Siemens, 2011). Meso-level analytics also fit within the academic analytics category but the focus of meso-level analytics is on academic performance reporting, typically to administrators, funders, and for marketing purposes (2011).

Meso-level analytics. Meso-level analytics reside at the institutional level. If data are integrated rather than siloed within departments or divisions of the university, then

meso-level analytics can be used to view the system. The use of meso-level analytics is where versions of business intelligence (BI) may potentially influence academic analytics. For example, system and workflow trends are visible at the institutional level and utilized to serve customers and to predict future demands (Buckingham Shum, 2012).

Micro-level analytics. Micro-level analytics are the data where individual transactions occur. Academic analytics are comprised of learning analytic functions. Objects of analysis in learning analytics include predictive modeling, success and failure patterns on behalf of the student, and conceptual development in the course, ultimately benefitting the learners and faculty (Long, & Siemens, 2011). These are typically the data collected when a student logs onto the learning management system platform and begins engaging with digital education on an individual level (Buckingham Shum, 2012). Interventions for at-risk learners occur on the micro-analytic and learning analytic levels (Macfadyen, & Dawson, 2010). This study focuses upon learning analytics at the micro-level.

Embedded within the macro, meso, and micro layers are different types of learning analytics, distinct areas for future research and refinement. Among the multiple directions higher education analytics are headed include: learning management system (LMS) analytic dashboards, predictive analytics, adaptive learning analytics, social network analytics, and discourse analytics (Buckingham Shum, 2012). Learning management system dashboards are now available for front end use, packaging student time and interactions with Blackboard or LMS vendor platforms.

Together, aggregate data communicates at-risk learner behaviors to faculty. The accuracy of at-risk learner alerts is based upon how much digital activity the faculty member incorporates in the faculty member's class. For example, if the instructor uses the Blackboard platform to house course readings and a learner downloads the work to the learner's iPad and Kindle applications, the student may not return to the LMS. This behavior could trigger the at-risk alert even though the student may be keeping up with the course assignments.

How learning analytics connect to this study. Learning management systems provide data that support students before the faculty, the institution, and perhaps student are even aware. Thousands of student data transactions reside on the LMS platform from one class alone (Picciano, 2012) and ongoing research is dedicated toward making sense of the ways a student's static and dynamic student behavior may statistically predict poor course performance. Early research points to specific data variables that begin to inform these predictive learning analytics.

One example is the M-STEM Academy, aimed at increasing academic success and retention of students who, for reasons of socioeconomic status, first generation college status, racial or gender bias, or lack of rigor in their high school preparation, might not be successful at a highly competitive, elite research university (Lonn, Krumm, Waddington, Teasley, 2012).

> Analysis of LMS tracking data from a Blackboard Vista-supported course identified 15 variables demonstrating a significant simple correlation with student final grades. Regression modelling [sic] generated a best-fit predictive model for this course which incorporates key variables such as total number of discussion messages posted, total number of mail messages sent, and total number of assessments completed and which explains more than 30% of the variation in student final grade. Logistic modelling

[sic] demonstrated the predictive power of this model, which correctly identified 81% of students who achieved a failing grade (Macfadyen, & Dawson, 2010, p. 588).

The future of learning analytics includes social learning, a deeper subset of learning analytics. Social analytics goes beyond the boundaries of the classroom, incorporating social networking and communities on formal and informal levels. The rationale behind breaching the boundary between the academic and personal environments is to fully understand the environment of the learner. Institutions can use environmental data to inform decisions about the institution and educational objectives (Ferguson, & Buckingham Shum, 2012). This study focused only on the classroom and blended learning environment and as such, did not explore social learning analytics.

Predictive analytics are increasingly available to Blackboard Learning Management System users, and can alert faculty of individual students who may need additional support (Blackboard, 2014). These predictive analytics are available but underutilized by faculty at SDSU. Picciano (2012) explains the course management system (CMS) warning system.

> In online courses, CMSs routinely provide course monitoring statistics and rudimentary early warning systems that allow instructors to follow up with students who are not responding on blogs or discussion boards, not accessing reading materials, or not promptly taking quizzes. These course statistics are maintained in real-time, and instructors can review them as often they wish. Again, students who are not as engaged as they should be can be sent an email expressing concerns about their performance. (p. 14)

San Diego State University has begun to use and measure the effects of predictive analytics to initiate course interventions in support of student success. These interventions are informed by technology use the classroom (clicker points) and learning management system engagement. Alerts are sent to students who do not receive clicker

points during live class sessions, receive low test scores and cumulative grades, and those students who do not complete online quizzes. The "triggers" are based upon statistically significant findings demonstrating that participation in these activities are predictors of positive student performance outcomes. Students receive email messages from their faculty member apprising them of the statistical probability of receiving a low grade based upon their current course performance, and encouraging them to participate in the future (Whitmer, Dodge, & Frazee, 2014).

Overview of the Literature

Although there are budgetary constraints within California's public higher education system, priority has been given to the identification and alleviation of slowing degree paths for students caused by bottlenecks that pose a threat to California's economy as each one-dollar invested in the CSU system stands to yield $23 in enhanced earnings of CSU alumni. As CSU campuses attempt to resolve bottleneck courses individually, the work that is being done varies, but faculty who choose to move into a blended learning environment are looking to the Sloan Consortium and best practices among other CSU campuses.

The CSU Chancellor and the Governor have made the movement toward blended learning pedagogy attractive by funding technologies on campus, incentivizing those who are exhibiting best practices to share their experiences with other faculty and campuses, and by supporting statewide online textbook and library initiatives. What the literature does not discuss is the impact that the strategies to alleviate bottleneck courses may have upon students and the institution. When students matriculate faster in a blended learning

course environment, does that necessarily mean they are ultimately successful in navigating through the bottleneck?

Although there is evidence of progress in this emerging field, blended learning is still in its infancy. Existing gaps in the literature include studies of blended learning environments, fiscal measures, and evaluation of course outcomes. Although learning analytics clearly helps support the analysis of blended learning outcomes, additional challenges remain. Learning analytics are messy, in that education produces a tremendous amount of data, but much of the data is not stored in the same place or in the same format. Since much of the learning analytics research comes from comparing a student's performance either at the individual, classroom, or institutional level, the data need to be in good condition to accurately process and analyze these nested levels.

Taken together, this literature review has revealed that there is currently no research that analyzes the demographic and learning outcomes of students in a California State University blended learning bottleneck course over time. Further, there is no research that observes the learning analytics of students who take a large-scale blended learning course in the CSU system. Finally, there are few explanatory research designs dedicated to the study of blended learning and learning analytics.

CHAPTER THREE

METHODOLOGY

This study was an evaluation of a large-scale blended learning bottleneck psychology course at San Diego State University, an impacted California State University campus. The site for the study was ideal for a number of reasons; for example San Diego State has the fourth largest population within the CSU system, and The College of Sciences is the second largest college (College of Business is the largest) on the campus with 4,682 students (San Diego State University Analytic Studies and Institutional Research, 2014). Additionally, the Department of Psychology represents the largest undergraduate major with 1,637 declared students and the Psychology 101 sections in the study represent the largest classes on the SDSU campus (M. Laumakis, personal communication, 2014).

Although psychology is a popular undergraduate major, students still struggle to pass the classes. A CSU study of the top 22 high demand, low success courses includes a number of psychology classes, while a systemwide study of CSU psychology courses revealed that 13% of students who take the course receive a repeatable grade of C- or below (San Diego State University Analytic Studies and Institutional Research, 2014; The California State University Office of the Chancellor, 2013). To provide a sense of scale, the course studied in this research, Psychology 101, accommodates approximately 1,000 students in two course sections taught by Dr. Laumakis each semester (M. Laumakis, personal communication, 2014).

The mixed method study employed a sequential explanatory research design in response to the four research questions (Creswell & Plano Clark, 2010). Research

questions one through three were explored using quantitative analysis, while question four was addressed using a qualitative research design. Specifically, this research employed logistic regression analyses of 18,254 individual demographic data records, paired with smaller samples of student performance observations, to analyze trends in the blended learning introductory Psychology 101 course at SDSU. The purpose of analyzing the relationships of student demographics coupled with how those students perform in the psychology class was to take a closer look at the student populations impacted by blended learning, and to understand more about the students who are ultimately successful and those who are not successful in the course and the reasons why.

Data Descriptions

Student course performance and demographic data were collected from classes instructed from Fall 2006 to Spring 2014, a total of 18,254 students. Demographics included, among other variables, race/ethnicity, age, class year, institutional transfer status, and socioeconomic status. A questionnaire was sent to 1,057 students who took Psychology 101 between Fall 2012 and Spring 2014 based upon statistically significant measures from the quantitative research. Qualitative methods followed the quantitative analysis in the form of five student interviews in order to provide a naturalistic explanation for the potential outcomes of the quantitative data (Patton, 2002). Each of the research questions and the corresponding methodology are detailed below.

Student demographic data. A second data set came from the SDSU Student Information Management System database (SIMS/R). Student names were redacted from both data sets and student ID numbers were used as unique identifiers to pair student demographic data with course performance data within the Statistical Package for the

Social Sciences (SPSS). Student demographic data originated from student applications

for admission to SDSU and academic record data. These data included: gender, ethnicity,

class year, Compact for Success (CS) participation, academic probation status, declared

academic major and minor, age, financial aid eligibility and participation in the

Educational Opportunity Program (EOP) as proxies for low socioeconomic status. See

Appendix C for a complete list of variables used in the study.

Student performance data. The study employed a quantitative analysis of

student performance data from one introductory SDSU psychology course facilitated

through a blended learning pedagogy. The course was taught by the same faculty

member beginning in the Fall semester of 2006 and repeated during each fall and spring

semester through Spring 2014, a total of 16 classes. Student course performance and

demographic data originated from two sources. One data set was retrieved from the

archives and downloaded from the Blackboard Learning Management System. This data

set contained student course performance observations from the psychology course which

included: exam scores, clicker points, Learning Curve assignment points, extra credit

participation, and final student grades for those who completed the course. See Appendix

C for all of the performance variables used in the study. Student RedID identification

numbers were used as unique identifiers when working with both data sets.

Quantitative Research Questions and Analysis

Three logistic regression models were estimated from student course performance

and descriptive student record data to assess the extent to which these measures helped

explain variation in course outcomes.

Research question one. The first research question asked to what extent student demographics can explain variation in the course withdrawal behavior of students enrolled in a blended learning undergraduate psychology course at San Diego State University. Specifically, can student demographics explain variation among those students who completed the course and those who dropped the course?

The question was addressed through an examination of 18,254 students' course persistence using a binary logistic regression. When students registered for Psychology 101 they have four options, they can withdraw from the course after the drop deadline without receiving a refund, withdraw with a partial tuition refund, withdraw with a full course refund, or stay and complete the class.

The original study design called for a multinomial logistic regression including each of these four options, but a close analysis of the data showed that only two students missed the deadline to withdraw from the course a receive a partial refund. All other students withdrew before the drop deadline stipulated by the university, about 10 days after the semester begins. The students who withdrew from the course past all of the deadlines received a "W" on their record and still have to take the psychology class or an equivalent. There were 272 of these students and they were coded with the students who did not receive grade points for taking the course: No Credit (NC), and those who received Incompletes (I) or failing grades (F), since the W still appears as a mark on the students' transcripts. See Appendix D for SDSU University policies regarding grade assignments and definitions.

Since nearly all of the students remained in the course or dropped the course before the university deadline, the model was redesigned as a binary logistic regression, measuring those students using the two sub-research questions below:

1. Which students withdrew from the course with a full refund?

2. Which students completed the course?

Research question two. The second research question used a subset of the students used in the first research question, those students who completed the undergraduate psychology course, to examine the extent to which student demographics and internal course performance data can explain variation in those students who received a passing grade versus students who received a repeatable grade of a C- or lower. See Appendix D for SDSU policies regarding course forgiveness.

A binomial logistic regression model was also used to address this research question. Taken together, student demographic and performance data were used to estimate a model that distinguished between students who successfully completed the course (defined as receiving a non-repeatable grade of C or higher) and those students who received repeatable grades lower than a C.

Since the predictive power of the demographic data alone was not high (Model One), more about that in Chapter Four, a decision was made to add performance variables from students who took Psychology 101 between Fall 2010 and Spring 2014, to the model. Complete Blackboard data from before 2010 were not available, so the student observations were restricted to 5,447 students, which are 12,807 fewer than those measured in Model One. Although Model Two could have been estimated using the 10,207 student observations who remained in Psychology 101 and received a grade,

adding performance variables from the Blackboard Learning Management System including attendance and test grades was the most effective way to respond to the research question and to still retain generalizability in the model.

Research question three. The third research question also called for quantitative analysis. Among those students who received a non-repeatable grade in the course (a C or higher), to what extent can student demographics and internal course performance data explain variation in the final grades of students in the course? This question was explored using a linear regression to measure predictive relationships among another subset of the students from the previous research question – those who received a non-repeatable grade in the course, a C or higher. Since there were students who received lower grades, but remained in the course, in Model Two, these students' records were moved out of Model Three. There were 3,705 student observations in the third model and again, the regression population was large enough to be generalizable to the entire student population.

Research question four. Research question four asked about the experiences of students whose demographic data most significantly explained those students performance in the blended learning psychology course. The two most significant findings from the quantitative analyses informed the qualitative study student populations. The qualitative methods in this study were designed to explain significant outcomes of the quantitative analysis and to contextualize those outcomes through the use of student questionnaires and interviews (Creswell & Plano Clark, 2010). In other words, did student responses about their experiences in Psychology 101 support or contradict what the quantitative data outcomes reported?

Student Questionnaire Bridge

In order to respond to research question four, to understand more about the experiences of students who took Psychology 101, and to inform future interview questions, a short student questionnaire (6 questions) was emailed to 1,057 students who took Psychology 101 between Fall 2012 and Spring 2014. See Appendices E and F for the questionnaire and informed consent used for this phase of the study. The students who received the questionnaire were African American, Mexican American, and Filipino men and women. The three race/ethnicity categories were significant with gender as predictors of student success throughout the three models in the study. When students responded to the questionnaire, the final question invited them to volunteer for an interview to learn more about their experiences in PSY 101.

The questionnaire was designed using the Qualtrics Online Survey Software Program. Based upon the explanatory design of the study, questions were formulated using findings from the quantitative outcomes and the literature and focused upon student motivation, communication and participation in Psychology 101. An example of one of the questions is as follows: "What factor or factors motivated you to enroll in Psychology 101 as a blended learning/hybrid (part online, part classroom) course? (Please check all that apply.)"

1. I liked the online option.

2. It was convenient to go to class one day and attend online the other day.

3. It was the only Psychology 101 course available.

4. It was the only class that fit my schedule.

5. I heard about it from a friend/classmate.

6. A friend/classmate was also taking the class.

7. I already took the class and was repeating it to earn a higher grade.

8. Other (Please explain)

The questionnaire had face validity; construct validity; and sampling validity, but it was not designed as a reliable survey instrument.

Students who took Psychology 101 were typically in their first year of study and those students were also still at SDSU after two years. Therefore, students who took the psychology class in the school years 2012-13 and 2013-14 were selected to receive the email questionnaire. Students were also more likely to recall their experiences in the course by only asking them to remember as many as two years back.

Analysis of student questionnaires. Student questionnaires were analyzed in two ways. First, the number of completed surveys was tabulated to determine the response rates. Next, the responses to each question were analyzed for trends using the reporting tools in the Qualtrics system, these included frequencies and crosstab analysis. Students who volunteered to be interviewed shared their email addresses and those were utilized to contact students and begin the interview process.

Qualitative Analysis

The explanatory research included student interviews, employing a semi-structured design to complement the emergent nature of each student's story (Patton, 2002), each lasting approximately 30 minutes. The interviews were conducted with informed consent (see Appendix F) and took place on the San Diego State University campus since all of the five interview participants were still attending school. All five students were Mexican American as there was only one respondent each from African

American and Filipino American students. All of the interview participants were former Psychology 101 students who completed the student questionnaire and elected to be interviewed. The semi-structured interview design included questions as follows:

1. What did you think about taking Psychology 101 in a blended learning (partially online, partially in-class) format?

2. When you attended the course online and on campus, did you do things the same way? For example, always log on from the same location, or at the same time. Or did you sit in the same place or with similar groups of people when you attended class in person?

See Appendix G for the interview guide submitted to the institutional Review Board (IRB) as part of the IRB modification that followed the quantitative findings.

The interviews were recorded, transcribed and analyzed using a holistic coding technique. Students were not incentivized to participate in the questionnaire or the interview process, but interview participants were sent a thank you note and token of appreciation, a $15 Amazon or Starbucks gift card.

Analysis of student interviews. Each interview was analyzed independently using a holistic coding technique. Thematic codes were assigned to frequent responses, and direct quotations were selected to illustrate a student's exact description of an experience or opinion. Codes were generated from initial review of the transcripts and included 11 main themes, which are explained in Chapter Four. Analysis of thematic convergence and divergence was important during this process between interviews and keeping the quantitative outcomes in mind. Information regarding student best practices

and at-risk course behavior surfaced in the individual interviews, providing rich description to the answers for research question four.

Document analysis, faculty and personnel interviews. Interviews with faculty and university personnel served only to inform the study design and to navigate the CSU system and San Diego State University policies and procedures for data collection. Key conversations took place with Psychology 101 faculty member Dr. Mark Laumakis, the Director and Associate Director of Instructional Technology Services, the University Registrar, and an Enrollment Services Analyst and faculty member. Additionally, document analysis served to inform a detailed understanding of the many components involved in the study. Documents included: minutes from CSU Chancellor Office and Board of Trustees meetings; SDSU grade, and university withdrawal procedures and tuition policies; Psychology 101course syllabi, university and CSU budget documents; enrollment statistics, and CSU-related policies, both pending and passed in the California Legislature.

Overview of Research Design and Methodology

This explanatory study set out to explore quantitative data consisting of aggregate student demographic and performance variables. After conducting a series of logistic regressions to address research questions one through three, data from the most significant relationships were used to deepen the research through qualitative inquiry directed at answering research question four. To bridge the quantitative and qualitative phases of the study, an email questionnaire was sent to students within the two most significant groups from the regression analysis outcomes, and who also took the Psychology 101 in the 2012-13 and 2013-14 academic years. The questionnaire asked

students if they would be interested in providing a student interview to further inform the research.

These data helped articulate some of the course outcomes, the demographic trends, and the lived experiences incurred by students in the blended learning Psychology 101 class. This research also provided empirical evidence of activities and predictive relationships within Psychology 101, which will hopefully provide support for the efforts California State University students, faculty, and administrators are employing to alleviate bottleneck courses within the CSU system. More importantly the research addressed potential risks that accompany this relatively new way of learning and teaching in higher education. Next, Chapter Four reports on the study outcomes.

CHAPTER FOUR

RESULTS

The purpose of this study was to determine if there are significant correlations between student demographic data including race/ethnicity, gender and socioeconomic status, and how those students perform in a blended learning psychology course, and to then further explore the findings qualitatively to explain why those relationships may occur. Through this research it was discovered there are indeed relationships between characteristics such as race, gender, high school performance, institution of origin, and students' overall student course retention, pass/fail outcomes, and final outcomes.

This chapter reports findings from the quantitative and qualitative data collected and analyzed using an explanatory sequential design. Phase One consisted of a quantitative analysis of demographic and performance data for students who registered and/or completed Psychology 101 (PSY 101) at San Diego State University (SDSU) between Fall 2006 and Spring 2014. Next, Phase Two of the study included a deeper analysis of significant findings through the administration of an online questionnaire sent to students who fit specific characteristics and who took PSY 101 between Fall 2012 and Spring 2014. In Phase Three, a set of interviews was conducted with students who completed the questionnaire and either passed the course or received repeatable grades (C- or below) to provide a more nuanced understanding of the unmeasured factors that students suggested influenced their overall course performance. A final conclusion summarizing all of the findings is found at the end of the chapter.

Phase One Data

Since the study design required student demographic and course performance data, these two data sets were extracted from different units and databases at SDSU and then combined for analysis. Student demographic data were collected from SDSU Enrollment Services and the same course periods, sections, and schedule numbers were utilized to request student performance data from Instructional Technology Services. Somewhat surprisingly, these two sets of data are not traditionally analyzed together. The siloed data were cleaned, rendered compatible and merged using the Statistical Package for the Social Sciences (SPSS). Three unique identifiers were used to pair the students' records with their course performance: student RedID, the period when the student enrolled in the course, and the section number selected for that period. After the two data sets merged, frequencies were run to error trap and verify that the data were successfully paired.

Enrollment services data. Enrollment Services provided a report of SIMS/R data that included any student with fall or spring enrollment history in PSY 101 with faculty member Dr. Mark Laumakis. The Excel file included self-reported student responses from SDSU admission applications and student record data. The data came with a codebook (Appendix H) that defined the 33 variables with number codes and abbreviations assigned to the data for university use and Internal Postsecondary Education Data System (IPEDS) reporting. A total of 18,254 student records were returned with the report. All of the student observations were included in Model One of the study while subsets of the population, specifically students who completed the course, were analyzed in Models Two and Three.

Blackboard Learning Management System data. Personnel from Instructional Technology Services (ITS) extracted archived data from the completed PSY 101 courses. Originally, 43 unique PSY 101 schedule codes were requested, ranging from Fall 2006 to Spring 2014. Data included test scores, participation points, and extra credit points students earned in the class. Complete data were available for all of the above variables beginning in Spring 2010. These data included 5,447 individual student records and the performance variables used in the study, found in Table 1 below. Each of the four tests was worth a total of 120 points and average test scores were in the 73% range, or C-. The percentage of students who used their clickers in live lecture classes one through six were consistent, with the exception of the first class when an average of only 72% of students "clicked in." Many students were still purchasing course materials and working on their class schedules and either did not attend the first course, or they were reminded when they arrived that they needed to bring their clicker to class.

Table 1

SDSU Blackboard Learning Management System Student Performance Data

	Psychology 101 Student Performance Variables			
Variable Category	Independent Variable	Min/Max	Mean Score	Percentage
Course Exams				
	Test One	0-120	87.19	73%
	Test Two	0-120	87.33	73%
	Test Three	0-120	82.8	69%
	Test Four	0-120	92.39	77%
Clicker Points		Frequency		Percentage
Clicker 1	Attended	3925		72%
	Absent	1522		28%
Clicker 2	Attended	4602		85%
	Absent	845		16%
Clicker 3	Attended	4563		84%
	Absent	884		16%
Clicker 4	Attended	4553		84%
	Absent	894		16%
Clicker 5	Attended	4596		85%
	Absent	851		16%
Clicker 6	Attended	4706		86%
	Absent	741		14%

Note. Clicker points serve as a proxy for attendance.; n=5,447

Data Frequencies

Within the 18,254 student observations were 6,397 men and 11,857 women together with a mean age of 19 years. White students accounted for 38.3% of the group and Mexican American students were the second largest ethnic group representing 22.1% of the total course population. On average 1,141 students registered for PSY 101 each semester with fewer students registering in the spring semesters than in fall. See Appendix I for PSY 101 course registration by semester and year. A majority of students, 88.3%, enrolled in the course originated from California high schools.

More than half of the students were eligible for financial aid and 14.6% were enrolled in the Equal Opportunity Program (EOP), which is designed to retain low-income and educationally disadvantaged students (SDSU, 2015). Distance education and blended learning course popularity and availability have steadily increased over the past five years, and many students had experience taking one or more of these courses before enrolling in PSY 101, illustrated here in Figure 4.
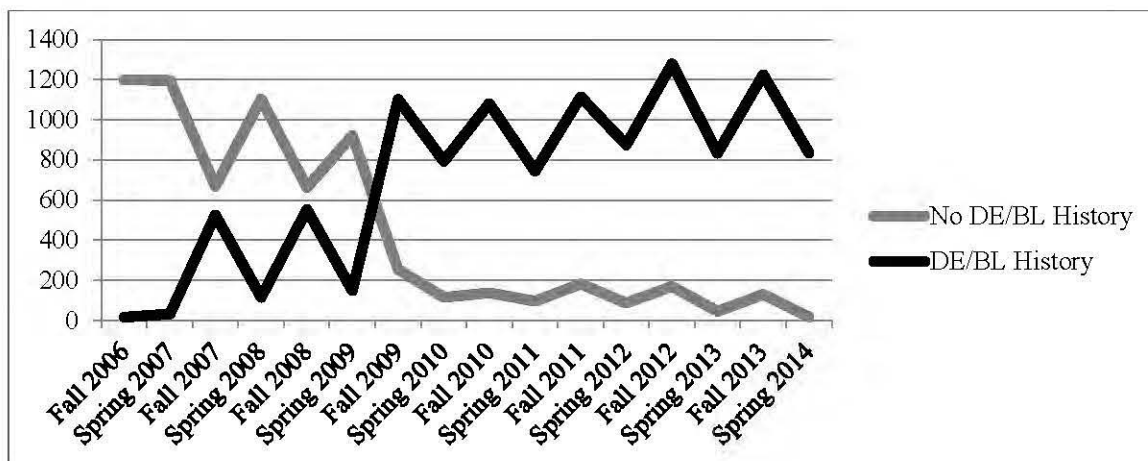
Figure 4. Distance education/blended learning (DE/BL) activity growth from 2006-2014.

Finally, 17% of students who enrolled in PSY 101 had one or more instances of academic probation on their student records. A full accounting of independent variable frequencies for the entire class population and the subset of students who attended from 2010-2014 can be found in Table 2 below.

Table 2

SDSU Enrollment Services Independent Variables and Frequencies

		Entire Class Population N= 18,254		2010-14 Student Subset n= 5,447		
Variable Category	Independent Variable	Frequency	%	Independent Variable	Frequency	%
Race/Ethnicity						
	African American	854	4.7	African American	228	4.2
	American Indian	72	0.4	American Indian	16	0.3
	Asian	846	4.6	Asian	240	4.4
	Filipino	1849	10.1	Filipino	526	9.7
	Mexican American	4041	22.1	Mexican American	1397	25.6
	Multiple Ethnicities	699	3.8	Multiple Ethnicities	333	6.1
	Other Hispanic	938	5.1	Other Hispanic	321	5.9
	Other/Not Stated	1312	7.3	Other/Not Stated	293	5.3
	Pacific Islander	107	0.6	Pacific Islander	14	0.3
	SE Asian	539	3	SE Asian	162	3
	White	6997	38.3	White	1917	35.2
Gender						
	Male	6397	35	Male	1871	34.3
	Female	11,857	65	Female	3576	65.7
Age (continuous variable)		19			19	
Citizenship and Language						
	US Citizen	17,390	95.3	US Citizen	5184	95.2
	Other Citizenship	864	4.7	Other Citizenship	263	4.8
	ESL	154	0.8	ESL	50	0.9
Socioeconomic Indicators						
	Financial Aid Eligibility	9737	53.3	Financial Aid Eligibility	3084	56.6
	EOP Enrolled	2675	14.7	EOP Enrolled	873	16
Matriculation Status						
	Freshman	8408	46.1	Freshman	2119	38.9
	Sophomore	6072	33.3	Sophomore	2212	40.6
	Junior	2532	13.9	Junior	819	15
	Senior	1242	6.8	Senior	297	5.5
Academic Standing						
	Total GPA (continuous)	2.68		Total GPA (continuous)	2.79	
	Total Units Earned	40		Total Units Earned	42	
	Academic Probation	3171	17.4	Academic Probation	679	12.5
Institution of Origin						
	CA Comm. College	652	3.6	CA Comm. College	133	2.4
	Non-CA High School	1259	6.9	Non-CA High School	433	7.9
College Prep Indicators						
	Compact for Success	1459	8	Compact for Success	631	11.6
	AP Credit	6972	38.2	AP Credits	2480	45.5
Distance Ed/Blended Learning						
	Course History	11,269	61.7	Course History	5415	99.4
Psychology 101 Registration						
	Fall	10,294	56.4	Fall	3329	61.1
	Spring	7960	43.6	Spring	2118	38.9

Data Inclusion

Of the 18,254 records many students had duplicate entities. Using the student's RedID as a unique identifier those 3,642 student records were isolated and analyzed. Two potential scenarios for these students were determined, and each of them could occur more than once.

The first scenario involves the student registering for PSY 101 and dropping the course before the semester began. In scenario two the student adds and drops the course, reenrolls, and then completes the course receiving a grade in that semester or at a later date. Of the 3,642 students with duplicate entities 1,801 received a grade in the course. The remaining 1,841 duplicate entities appeared without a grade, indicating the student only had add/drop PSY 101 activity on their student record. Students who had add/drop data and no class participation means that those students either considered taking PSY 101, attended a class or two and then withdrew, or they were adding other courses to their schedule and withdrew right away. Some of the time stamps on the student add/drop records indicated that the student added and dropped the class on the same day, sometimes more than once. Initially, only a student's first grade or add/drop record was retained for the study in the case of a duplicate record. Upon further consideration, all duplicate were records reintegrated into the data set for analysis since these entities were not errors but evidence of student behavior within the course.

Measuring each instance of student involvement within PSY 101 was determined to be a more accurate way of looking at bottleneck and performance issues within this study. In some cases a student record appeared up to seven times. Course supply and demand is at the heart of the bottleneck issue, and students who took the entire course

more than once exhibit symptoms of those involved in student readiness and curricular

bottlenecks. Students who add and drop the course multiple times may be exhibiting

symptoms of those involved in advising and scheduling bottlenecks. Ultimately there

were 14,612 (80%) unique student records within the total 18,254 records. Of the total

18,254 students who were enrolled in the course between Fall 2006 and Spring 2014,

13,765 received a grade and 4,489 students dropped the course.

Modeling Strategy

Although predictive analytics are not new within the education sphere, blended

learning literature does not yet have a general model that might inform the selection of

key independent variables. As such, stepwise regression was used to build the three

models. Backward elimination began by adding all demographic data variables from

Enrollment Services into the model and removing each statistically insignificant variable

one by one to improve the model. Categorical data for race/ethnicity and the semester

and year when the course was administered were kept together regardless of significance.

For example, the variable for students who self-identify as Asian was not significant in

any of the models, but it was retained with the race/ethnicity variables throughout the

study. Independent variable codes can be found in Table 3 below.

Table 3

SDSU Independent Variable Coding Specification

Variable Category	Independent Variable	Code
Race/Ethnicity		
	American Indian	0 if other, 1 if American Indian
	African American	0 if other, 1 if African American
	Asian	0 if other, 1 if Asian
	Filipino	0 if other, 1 if Filipino
	Mexican American	0 if other, 1 if Mexican American
	Multiple Ethnicities	0 if other, 1 if Multiple Ethnicities
	Other Hispanic	0 if other, 1 if Other Hispanic
	Other/Not Stated	0 if other, 1 if Other/Not Stated
	Pacific Islander	0 if other, 1 if Pacific Islander
	Southeast Asian	0 if other, 1 if Southeast Asian
	White	0 if other, 1 if White
Gender		0 if Female, 1 if Male
Age		Continuous Variable
Citizenship and Language		
	US Citizen	0 if other, 1 if Citizen
	ESL	0 if other, 1 if English is Second Language
Socioeconomic Indicators		
	Financial Aid Eligibility	0 if other, 1 if Eligible
	Equal Opportunity Program	0 if other, 1 if EOP Enrolled
Matriculation Status		
	Freshman	0 if other, 1 if Freshman
	Sophomore	0 if other, 1 if Sophomore
	Junior	0 if other, 1 if Junior
	Senior	0 if other, 1 if Senior
Academic Standing		
	Total GPA	Continuous Variable
	Total Units Earned	Continuous Variable
	Academic Probation	0 if other, 1 if Probation History
Institution of Origin		
	CA Comm. College	0 if other, 1 if CA Community College
	Non-CA High School	0 if other, 1 if Non-CA High School
College Prep Indicators		
	Compact for Success =1	0 if other, 1 if Compact for Success Scholar
	HS AP Credits (AP) =1	0 of other, 1 if Advanced Placement Credits
Distance Ed/Blended Learning		
	Course History =1	0 if other, 1 if Dist. Ed./Blended Learning
Psychology 101 Registration		
	2006-2007	0 if other, 1 if Fall 2006
		0 if other, 1 if Spring 2007
	2007-2008	0 if other, 1 if Fall 2007
		0 if other, 1 if Spring 2008
	2008-2009	0 if other, 1 if Fall 2008
		0 if other, 1 if Spring 2009
	2009-2010	0 if other, 1 if Fall 2009
		0 if other, 1 if Spring 2010
	2010-2011	0 if other, 1 if Fall 2010
		0 if other, 1 if Spring 2011
	2011-2012	0 if other, 1 if Fall 2011
		0 if other, 1 if Spring 2012
	2012-2013	0 if other, 1 if Fall 2012
		0 if other, 1 if Spring 2013
	2013-2014	0 if other, 1 if Fall 2013
		0 if other, 1 if Spring 2014
Course Exams		
	Test One	Continuous Variable
	Test Two	Continuous Variable
	Test Three	Continuous Variable
	Test Four	Continuous Variable
Clicker Points		
	Clicker 1	0 if other, 1 if Attended
	Clicker 2	0 if other, 1 if Attended
	Clicker 3	0 if other, 1 if Attended
	Clicker 4	0 if other, 1 if Attended
	Clicker 5	0 if other, 1 if Attended
	Clicker 6	0 if other, 1 if Attended

Importantly, in two instances a student's institution of origin was added to the model without including the other institution variables. It was only significant in Model One, block one, which demonstrated that a student who transfers from a California Community College was more likely to drop the class than students who transferred from other institutions. An F-test was conducted to verify whether including all or none of the categorical data for a student's institution of origin would improve linear regression in Model Three. It was ultimately determined that the null hypothesis could not be rejected, and consequently none of the institutions of origin mattered in the regression.

As the models began to take shape, the blocks were organized as follows. Block one in each of the three models contains only those fixed characteristics that students' possess before they register for Psychology 101 (e.g. race/ethnicity, gender, high school AP credits). Block two in each of the models contains only temporal student characteristics during the semester when the student took Psychology 101 (e.g. EOP status, GPA, age). Block three only appears in Models Two and Three because those students completed the course and have performance data records. The students who completed the course from block one are included in block two, but the performance data were not included to measure student retention and attrition because the data were not relevant. Block three contains student performance variables that occurred during the first half of the course (e.g. test performance, clicker participation).

The decision to measure only the first half of the course was based upon two principles. First, by identifying at-risk students early in the course, the opportunity to create student success interventions increases. Second, the points a student receives in the class completely determines the student's final grade; as such, the inclusion of all

course grades would have resulted in perfect collinearity, in essence, undermining the statistical validity of any sort of regression model. The next section reports on the results of the three regression models.

Phase One: Regression Analysis

This section reviews the outcomes of three regression models designed to estimate student performance from demographic variables. Model One measures Psychology 101 student persistence and this section begins with a description of the variables that were added and eliminated from the model, followed by outcomes of the binary logistic regressions.

Model one analysis. The first block built within Model One was designed to measure a student's characteristics before the student began attending SDSU. These are primarily the items found on a student's college application, which included the student's self-identified race/ethnicity, the institution the student originated from, which was usually a high school or community college, the person's gender, and whether the student was transferring advanced placement credits from high school for credit at SDSU.

In the second block, variables from the student's college record were incorporated. These were considered the variables a student assumed when the student took PSY 101. Characteristics included Equal Opportunity Program participation, the student's age at the beginning of the semester when the student took PSY 101, the total number of units the student had at the time they took the class and the student's total SDSU grade point average. This GPA measure proved to be very important throughout the study. Binomial logistic regressions were run in an effort to create a predictive model for students who would ultimately remain enrolled and those who would drop PSY 101.

The dependent variable used in this model (DV1) was transformed to Enrolled Retained = 1 and Enrolled Dropped = 0, using the Class Status variable from the Enrollment Services data set. A Class Status code of 0 indicated that the student took the entire course. There were 13,493 students who completed the class. Students with a Class Status code of 1 withdrew after the university deadline and received a "W" in the course (n=272). A "W" qualifies as a repeatable grade so these students were coded into the Enrolled Retained category. Students whose Class Status was coded 2 indicated that they withdrew before the university deadline (n=4,489).

Block one. Model One consists of two blocks. The first block includes variable data from a student's application and student record when the student arrived at San Diego State. The following variables were significant predictors (p < .001) of student retention and attrition activity in PSY 101 before the university designated class drop deadline: ethnicity, citizenship status, whether the student participated in Compact for Success (a college preparatory program initiated in high school), and the student's institution of origin.

Students who self-identified on their SDSU admission application as: African American (β = -.334), Mexican American (β = -.162), Southeast Asian (β = -.619), or Filipino (β = -.248) were more likely to drop Psychology 101 than the White student reference group. The model produced a Cox & Snell R Square of .010 and successfully predicted 75.4 percent of cases.

Block two. Block two also included variables a student assumed during the semester the student took PSY 101. These characteristics included the following: the periods when a student took the course (i.e., Spring 2007, Fall 2013), the cumulative

number of units a student earned up to entering the course, whether the student was enrolled in the Equal Opportunity Program (EOP) during the semester of the course, and whether the student had distance education or blended learning units on the student's record when he or she began the course. The stepwise regression modeling strategy improved the model to only include statistically significant variables and those belonging to categories where one or more variables were significant. The complete model with blocks one and two yielded a stronger R Square of .15 and predicted 81% of cases.

Using stepwise regression, the model was not improved by adding financial aid eligibility or students whose second language was English. This was an unexpected outcome since student Equal Opportunity Program Participation and United States citizenship were significant predictors in the model.

Model one outcomes. Although the overall predictive power of Model One is weak, there were a number of significant findings that remained consistent in both blocks and throughout the rest of the study. Many of these predictors and the direction of the coefficients are supported by the higher education student performance literature (Tinto, 1984). California Community College transfer students are more likely to drop the course before the university deadline (β = -.704) along with students participating in Compact for Success (β = -.270) and Equal Opportunity Programs (β = -.207). There was also a small but significant inverse relationship between the total number of units a student earned and course retention (β = -.010), meaning that the more units a student has, the more likely the student is to drop the course.

However, students with U.S. citizenship ($\beta = .345$) and distance education and/or blended learning course history ($\beta = 2.98$) were more likely to remain in PSY 101. See the significant findings in Table 4 below.

Table 4

Significant Predictors of Student Retention and Attrition in Psychology 101

	Model One Regression Output				
	Block One			Block Two	
Independent Variables	β	Sig.		β	Sig.
African American	-.33	.000		-.22	.019
Mexican American	-.16	.001		-.03	.567
Southeast Asian	-.62	.000		-.48	.000
Filipino	-.25	.000		-.28	.000
Citizenship	.38	.000		.35	.000
Compact for Success	-.27	.000		-.27	.000
CA Comm. College Transfer	-.70	.000		-.27	.007
Total Units Earned				-.01	.000
Equal Opportunity Program				-.21	.000
Distance Ed/Blended Learning				2.98	.000
Fall 2006				2.77	.000
Spring 2007				2.80	.000
Fall 2007				2.18	.000
Spring 2008				2.68	.000
Fall 2008				2.03	.000
Spring 2009				2.47	.000
Fall 2009				-.07	.430
Spring 2010				.29	.008
Fall 2010				.30	.003
Spring 2011				-.07	.488
Fall 2011				.10	.313
Fall 2012				-.53	.000
Spring 2013				-.25	.012
Fall 2013				-.40	.000

Note. N=18,254; $p < .001$

It is important to note that the effect size of distance education and blended learning history on a student's academic record reduced the predictive power of other

variables within block two of the model. As such, two race/ethnicity predictors from Model One were no longer significant: African American and Mexican students.

Adding the semester and year the students took Psychology 101 to the model demonstrated that some semesters had higher rates of attrition than others. Most notably, students who took Psychology 101 from Fall 2006 through Spring 2009 were much more likely to remain in the class. After that time period the only semesters that significantly predict student retention or attrition are Fall semester 2012 and 2013. More information is needed to understand why student retention was so high through Spring 2009, but there are two potential explanations from data provided by this study.

The first potential explanation is shown in Figure 4, earlier in the chapter, which illustrates the sharp increase of students who have a history of taking at least one distance education/blended learning (DE/BL) course and the downward trajectory of students who did not have a DE/BL course history. The intersection of these two populations occurs in between Spring and Fall 2009. Perhaps students with DE/BL class history were more likely to evaluate the class for a short period of time and then decide to drop it before the deadline.

The second possibility for the significant decrease in student retention is a subtle policy directive that came from the University. Dr. Laumakis began teaching Psychology 101 in a blended learning format in 2006. He created the new pedagogy for the class and evaluated the course both himself and with the support of the Sloan Consortium and their Quality Framework. Around 2009 SDSU mandated that Psychology 101 be instructed in a blended learning format in order to consistently accommodate the 1,000 students who would need to take the course each semester. Although students did not know about this

policy change it is possible that another variable that affected class retention was introduced to the course at the same time period which is not seen or measured in this research.

      Model two analysis. This section reviews the processes and outcomes of Model Two. This model is designed to determine the predictive potential of both student characteristics and learning analytics in relation to the likelihood that a student will pass or receive a repeatable grade (C- or below) in Psychology 101.

      Model Two consists of 5,447 student observations, 12,807 fewer than Model One. Although blocks one and two within Model Two could have been estimated using 10,207 student observations from the Enrollment Services data alone, block three measures specific learning analytic variables from the Blackboard Learning Management System. These data increase the predictive power of the model while maintaining enough student observations for significant and generalizable outcomes. Complete performance data were available for students who took the class between Spring 2010 to Spring 2014.

      Like Model One, Model Two was run as a binomial logistic regression since the two outcomes being measured were based upon a student either passing the course or receiving a repeatable final grade in PSY 101. The dependent variable used in this model (DV2) was transformed by first coding grade values from lowest grades to highest, 1-17.

      These grade codes included all grades from A through F and the additional marks that are assigned based upon special circumstances. Grades below a C- and the following codes: Unauthorized Withdrawal (UW), Withdrawal (W), Incomplete (I), and No Credit (NC) are considered repeatable grades. A repeatable grade means that the student could take the course again, which weighs upon the existing bottleneck. These grade codes, 1-9

were assigned a dummy variable of 0 = Repeatable Grade. Similarly, Non-repeatable

grades included A through C and Credit (CR). Grade codes 1-9 were assigned a dummy

variable of 1 = Non-repeatable.

 Block one. Model Two has three blocks. Again, the blocks within each of the

three regression models measure student characteristics before the student entered SDSU,

followed by characteristics a student assumed when he or she registered for PSY 101, and

in Models Two and Three an additional block estimates the contribution of the student's

early course performance variables (e.g., class attendance, test scores). Both Enrollment

Services and the Blackboard Learning Management System archival data were used in

Model Two.

 Within block one the following variables were significant predictors of students

who received a non-repeatable grade and those who received a repeatable grade in PSY

101: ethnicity, gender, citizenship status, and students who transferred advanced

placement (AP) credits to SDSU. The model yielded a Cox & Snell R Square of .056,

predicting 70.7 percent of cases. Students who transferred AP credits from high school to

SDSU were more likely to receive a C or higher when compared to students who did not

transfer units ($\beta = .674$).

 A number of ethnicity variables were significant in block one. There was a

negative correlation between students who self-identify as African American ($\beta = -.869$),

Mexican American ($\beta = -.960$), Other Hispanic ($\beta = -.758$), and Filipino ($\beta = -.533$), and

receiving a non-repeatable grade in the course. This means that students who identified

within these race groups on their SDSU application were more likely than students who

identified as White to receive grades of C- or lower in PSY 101. The reasons why a

student would not perform as well in a course based partially upon the student's race/ethnicity is a concept that is explored further in the student interviews.

Block two. Block two provided much more predictive power and included student characteristics from the semester when the student was enrolled in PSY 101. Student grade point average (GPA), age and student probation history were all significant predictors of student success in the course. Grade point average had the largest positive coefficient (β = 3.81) indicating that students who are already doing well in their classes are more likely to pass Psychology 101. Conversely, students who had an academic probation indicator on their record, current or past were less likely to receive a non-repeatable grade (β = -1.29; p < .003). Ethnicity, gender, and the positive effect of AP credits, however, were not statistically significant in block two. The model including blocks one and two yielded an R Square of .395 and successfully predicted 83.1 percent of cases.

Block three. Block three of Model Two is designed to estimate the value of early student success or at-risk variables with the use of learning analytics from the psychology course. These include: attendance up to and including the first and second exams, and student performance on those exams. As mentioned earlier, these learning analytic data were from classes administered between Spring 2010 and Spring 2014. However, there are randomly missing data for the Spring 2012 semester and in sections 3 and 6 of Fall 2010; these data were not used in the subsequent analysis.

The predictive power of block three increased from that of block two; specifically, the R Square was .491, and 88.1 percent of cases were successfully predicted. The only remaining block one variables with moderate statistical significance

were gender (β = -.294, p < .004), and age (β = -.097, p < .003). These variables indicate that both men and older students were less likely to be successful in the course.

The most valuable information in block three comes from performance related measures including attendance. Classroom clickers are the remote devices students use to verify their attendance and to answer questions as a large lecture audience. Attendance proxies were transformed from points awarded to students who "clicked in" to answer questions or to confirm their attendance during each of the live lectures in the first half of the course. All six of these instances of attendance were positive predictors of student success, and the coefficients steadily increase in the class sessions after Test One.

Similarly, students who attended Test One (β = 2.31) and Test Two (β = 3.11) were more likely to receive a non-repeatable grade in the course. However, students who scored in the lowest quartile of Test One (β = -1.36) and Test Two (β = -1.82) were significantly less likely to be successful. In other words, students are more successful when they attend the exams, which is intuitive. Those students who attend on exam days and do not perform well on the test are also likely to have repeatable grade outcomes with those students who do not attend at all.

In Model One there was a significant decrease in student retention between the Spring and Fall 2009 semesters. However in Models Two and Three distance education/blended learning history did not enter either model as a significant variable. Recall that both Models Two and Three were restricted to data from Spring 2010 to Spring 2014 only, so it is entirely possible that the high saturation of students with DE/BL history might render the variable insignificant. However, when blocks one and two of the Model Two were run using the complete data set for all students who

completed the course, the DE/BL variable was still insignificant, suggesting another explanation might be in order.

The semester when students took the class continued to show statistical significance in blocks two and three, with only Spring 2010 and 2011 remaining as significant predictors of lower student success compared to the Spring 2014 variable. Semester variables from Fall 2006 through Fall 2009 were removed from the model since those student records were not included in the analysis; only student records with Blackboard Learning Management System learning analytic data were included in those models.

Model two outcomes. It is not surprising that Model Two reveals that grade point average is by far the strongest determinate of whether a student passes or fails a course, and that adding the variable took most of the predictive power from other variables including race/ethnicity which were no longer significant at the $p < .001$ level. By incorporating learning analytics into the model the power not only increased, but the weight shifted from a student's demographic characteristics to how students perform as the most significant predictors of student success. The shift to learning analytics does not invalidate the findings that indicate demographic variables predict student course performance, but they are much stronger predictors. In Model Two student course success and failure are primarily based upon student class attendance and test performance. The outcomes are below in Table 5.

Table 5

Significant Predictors of Student Repeatable/Non-Repeatable Grades in Psychology 101

| | Model Two Regression Output | | | | | |
| Independent Variables | Block One | | Block Two | | Block Three | |
	β	Sig.	β	Sig.	β	Sig.
African American	-.87	.000	-.006	.976	.09	.705
Mexican American	-.96	.000	-.03	.844	.05	.738
Other Hispanic	-.76	.000	-.05	.801	.14	.527
Filipino	-.53	.000	.000	.998	.15	.406
Gender	.40	.000	-.18	.037	-.29	.004
AP Credits	.67	.000	.06	.496	.07	.508
Spring 2010			-.97	.000	-.70	.001
Fall 2010			-.94	.000	-.40	.072
Spring 2011			-1.09	.000	-.82	.000
Fall 2011			-.72	.000	-.51	.007
Fall 2012			-.64	.000	-.38	.046
Spring 2013			-.18	.329	.20	.342
Fall 2013			.02	.909	.16	.434
Grade Point Average			3.81	.000	2.90	.000
Age			-.16	.000	-.10	.003
Academic Probation History			-1.29	.003	-1.39	.003
Repeat Students			-.52	.000	-.55	.000
Probation/Repeat Students			2.39	.000	2.33	.000
Test One 25th Percentile					-1.36	.000
Test Two 25th Percentile					1.82	.000
Test One Attended					2.31	.000
Test Two Attended					1.11	.000
Clicker Session One					.52	.000
Clicker Session Two					.67	.000
Clicker Session Three					.58	.000
Clicker Session Four					.66	.000
Clicker Session Five					.84	.000
Clicker Session Six					.93	.000

Note. $n=5,447$; $p < .001$

Model three analysis. Model Three is designed to determine the predictive ability of both student characteristics and learning analytics in explaining the variance surrounding the final grades students received in Psychology 101. This third and final model consisted of 3,705 student observations. These are the students who remained enrolled in the course and received a final grade of C or higher. There were 1,742 students in Model Two who did not receive a non-repeatable grade of a C or higher,

representing 32% of the population who took PSY 101 between Spring 2010 and Spring 2014.

Model Three data were analyzed using linear regression analysis to determine if there were relationships between student demographic and learning analytic variables, and the exact grade those students received in PSY 101. Dependent variable three (DV3) was transformed by assigning grade values one through eight, the lowest grade being a C, and an A grade was assigned the highest value. There were 18 students who received credit in the course, but they did not receive a letter grade and as such, were coded as if they received a C.

Model Three also has three blocks based upon student characteristics before the student began attending SDSU, the student's demographic characteristics at the time the student took PSY 101, and finally the student's early performance in the course. Both Enrollment Services and archived course data from the Blackboard Learning Management System were used in Model Three.

Block one. The following variables were significant block one predictors of student final grades in PSY 101: ethnicity, gender, Compact for Success participants, and students who transferred advanced placement (AP) credits to SDSU. The first block yielded an R Square of .064. Each statistically significant variable had a negative effect, with the exception of students who transferred AP credits to SDSU as these students were still more likely to receive higher grades ($\beta = .735$). Once again the largest negative coefficients were those associated with grades assigned to African American ($\beta = -.633$) and Mexican American ($\beta = -.646$) students.

Block two. In block two, grade point average, total units earned, age, financial aid, and probation history variables were added to the model. The goodness-of-fit R Square measured .481 but the explanatory power of GPA (β = 2.79) overshadowed the other variables associated with PSY 101 final grades. The only other significant variables that emerged from the model were students who transferred AP credits to SDSU (β = .153) and students with more units received incrementally higher grades than newer students (β = .005). As an aside, because PSY 101 is a highly repeatable course, an interaction variable was created for students with probation history and more than one record for the class. Although probation history and the interaction variables were not significant in this model, students with more than one record (either an add/drop or course repeat) received lower grades than the first-time class taker population (β = -.288).

Block three. Just as block three in Model Two incorporates performance variables that occur in the first half of the course, these are also present in this final block of Model Three. These include student attendance during the first six sessions and during the first exam, and student performance on the first two exams. The third block yielded an R Square of .626. Significant positive coefficients included: GPA (β = 1.99), attending Test One (β = 2.42), and each of the six live class sessions.

Model three outcomes. Model Three demonstrates the strong correlation between student GPA and overall course performance, but the strength of the model comes from a closer look at the trends within the coefficients. For example, attending Test One (β = 2.42) is a much stronger determinate of a higher grade than attending Test Two, which was not a significant variable in Model Three (β = 1.30, p < .121) whereas poor performance, defined as scoring in the 25 percentile on the Test One (β = -.950) had less

negative impact upon a student's final grade than Test Two (β = -1.24). Table 6 shows the Model Three regression outcomes below.

Table 6

Significant Predictors of Grade Variation in Psychology 101

	Model Three Regression Output					
	Block One		Block Two		Block Three	
Independent Variables	β	Sig.	β	Sig.	β	Sig.
African American	-.63	.000	-.11	.303	.002	.989
Mexican American	-.65	.000	-.02	.770	-.01	.885
Gender	-.27	.000	-.00	.964	-.13	.002
Compact for Success	-.35	.001	-.06	.434	.07	.294
AP Credits	.74	.000	.15	.002	.12	.004
Grade Point Average			2.80	.000	2.00	.000
Total Units Earned			.01	.000	.004	.003
Repeat Students			-.29	.000	-.30	.000
Spring 2010			.74	.000	.49	.000
Fall 2010			-.75	.000	-.50	.000
Spring 2011			.64	.000	.46	.000
Fall 2011			-.62	.000	.44	.000
Fall 2012			-.52	.000	-.35	.000
Spring 2013			.35	.000	.13	.116
Fall 2013			-.12	.161	-.15	.037
Test One 25th Percentile					-.95	.000
Test Two 25th Percentile					-1.24	.000
Test One Attended					2.42	.000
Test Two Attended					1.30	.121
Clicker Session One					.40	.000
Clicker Session Two					.51	.000
Clicker Session Three					.41	.000
Clicker Session Four					.31	.000
Clicker Session Five					.50	.000
Clicker Session Six					.58	.000

Note. n=3,705; p=.001

Regression analysis conclusions. Within and among all three models, the following factors predicted student grade outcomes in Psychology 101. Student performance was significantly correlated with: race/ethnicity, age, citizenship, socioeconomic status (EOP), grade point average, units earned, distance education/blended learning experience, institution of origin, academic probation history, and earned advance placement (AP) credits. These demographic variables were then

combined with PSY 101 learning analytics, and the addition of test scores and attendance further strengthened the explanatory power of student performance. At this point in the study many of the demographic variables were significant, but none were stronger predictors of a student's overall success in the course than their own GPA and course exam scores and attendance, an intuitive outcome. This leads to the question, why are certain groups of students more successful in Psychology 101 than others?

Race/ethnicity variables predict student performance throughout Models One, Two and Three. African American, Mexican American and Filipino students stood out within the three models as large populations of students whose academic achievement warrants more study because they were consistently less successful than the White student reference group. Controlling for all other variables, these populations were statistically significant in the first block of each regression, with the exception of the Filipino student variable, which did not appear significant in Model Three. However, adding student record and performance variables in blocks two and three rendered the race/ethnicity variables insignificant. Oftentimes demographics are the only available data, but in this study the data set was rich, including students' grade point averages, units earned and course performance data. These variables were stronger predictors of the final grade outcomes. Taken together, the course performance and demographic analysis supported the decision making process for the next phase of the study.

Looking at the entire population, Filipino students were significantly more likely to drop the course while African American students and Mexican American students were more likely to receive repeatable grades of a C- or lower. All three groups were selected to receive a brief, online questionnaire to learn more about their experiences and

opinions of the course. It should also be noted that Southeast Asian students were significantly less successful in PSY 101. Although the population is not as large as the others (N=539), this is a group that also warrants future study. In fact, significant findings show that all minority groups are lower performers than the White student reference group.

Phase Two: Questionnaire

   Demographics. After the first phase of quantitative data analysis was complete, the findings from the regressions were used to learn more about the experiences of students who took PSY 101. Questionnaires were sent to students who self-identified on their SDSU application for admission as Mexican American, African American or Filipino, since they are at a statistically significant disadvantage throughout the study. These students were significantly more likely than the White reference group to drop the course; they were also more likely to receive a repeatable grade and less likely to receive higher grades than the reference group.

   Students who received the questionnaire (n=1,057) were among those who took PSY 101 between Fall 2012 and Spring 2014 (N=3,041). See Appendix E for the student questionnaire. This student population consisted of freshman and sophomores, on average 19 years of age, with a B- (2.84) grade point average. There were more female than male students, 66% female and 34% male, and more than half of the students were eligible for financial aid assistance. Nearly all of the students had at least one distance education/blended learning class on their student record (99%). Test scores for students who took PSY 101 between Fall 2012 and Spring 2014 were a little higher than the

student subset from 2010-2014, on average 75% (C), with 98% average attendance on test days.

Although the questionnaire is not generalizable to the entire population of PSY 101 students, these characteristics (with the exception of test and attendance data, which were unavailable) were reflective of the entire student population that received a grade in the course (N=13,765).

Questionnaire distribution and response. Students received the six-question survey via email and responded through a Qualtrics survey link. The largest response rate and population solicited were Mexican American females who received a non-repeatable grade in the psychology course. The second largest response also came from Mexican American females who received a repeatable grade.

Emails inviting students to complete the questionnaire were originally sent to 830 African American and Mexican American students and there were ultimately 148 respondents (18%). Upon further analysis of the regression model data, Filipino students were added to the questionnaire group because of their high likelihood of dropping PSY 101. This addition increased the solicitation total to 1,057 and subsequently decreased the response rate to 8% with only 17 Filipino student responses bringing the total to 165 student respondents.

Outcomes. Overall, student respondents reported that the convenience of attending class one day and attending online the other day was their primary motivation for taking PSY 101 (55%). That being said, students reported a stronger preference for the classroom lectures (47%), while 34% preferred both classroom and online lectures equally. Only 8% of students preferred the online class lectures. Students reported

primarily discussing quizzes and exams with other students (63%) and 16% of students reported they did not speak to other students in the class.

While students had a range of preferences and opinions about the course, the survey focused upon three main themes: students' motivations for taking the course, their preparation before and during the course, and the communication they had with other students throughout PSY 101. When questionnaire data were combined, the outcomes demonstrated the student experience in greater detail.

Motivation and preparation. For example, when students were asked, "What factor or factors motivated you to enroll in Psychology 101 as a blended learning/hybrid (part online, part classroom) course? Please check all that apply," a majority of students (55%) shared that, "It was convenient to go to class one day and attend online the other day."

Table 7

SDSU Student Questionnaire: Motivation/Preparation

		Preparation			
		I felt completely prepared to take Psychology 101 in a blended learning format	I felt somewhat prepared to take Psychology 101 in a blended learning format	I did not feel prepared to take Psychology 101 in a blended learning format	Total
Motivation	I liked the online course.	30	19	1	50
	It was convenient to go to class one day and attend online the other day.	48	38	4	90
	It was the only Psychology 101 course available.	5	15	12	32

When this question was examined using crosstab analysis with question four that touched on a student's self-reported level of preparedness for the class, a potential problem emerged. "Setting aside your final grade in this course, did you feel prepared to take Psychology 101 in a blended learning (hybrid) format?" Crosstab data show that 48 students who felt completely prepared to take the blended learning course also liked the

convenience of taking the class partially online. However, 38 students who felt somewhat but not completely prepared to take the course in a blended learning format were also attracted to the convenience of only attending class in person once a week.

Preparation and communication. According to the questionnaire, students who felt somewhat or not at all prepared to take the class reported lower levels of communication with other students. Conversely, students who did feel prepared for the class reported communicating with others about exams, homework, clicker points, and other course topics. The top three discussion items for students who reported feeling completely prepared to take the course were: quizzes and exams (46 responses), homework assignments (29 responses), and clickers (28 responses).

Communication and motivation. Students who reported they liked the convenience of attending PSY 101 were also more likely to talk to other students about quizzes and exams (55 responses). In fact, students who reported taking the class because they liked the convenience were the most communicative group according to the questionnaire. The least communicative groups were students who heard about the class from a friend, followed by those who reported they were retaking the class.

Table 8

SDSU Student Questionnaire: Communication/Motivation

		Communication							
	Homework	Tests	Attendance	Online lectures	Clickers	Technical support	Class lectures	Did not talk with others	Total
I liked the online option.	25	35	11	15	19	13	9	4	49
It was convenient	31	55	17	25	37	16	13	8	90
It was the only PSY 101 course available	14	25	3	14	14	11	5	10	43
Only class to fit my schedule	12	25	5	13	19	8	5	7	44
Heard about PSY 101 from a friend	7	16	2	7	11	9	2	1	19
Taking class with a friend	18	26	6	13	17	10	6	0	29
Repeating the class	4	6	1	3	5	2	3	1	12
Other	4	6	1	3	4	2	2	3	13
Total	52	92	20	47	58	30	21	23	165

Questionnaire analysis conclusions. Data from the questionnaire began to inform why students might choose to take Psychology 101 in a blended learning format. The crosstab analysis revealed information that began to fill in gaps that remained after the regression models were complete. For example, questionnaire crosstab data analysis demonstrated that students who did not feel prepared to take the course were also attracted to the convenience of attending one in-class lecture and one online session. When this theme was mentioned within the interviews, students shared their rationale behind the assumptions of timesavings and convenience within a blended learning class. The last question asked students if they would be interested in participating in an interview to share their experiences during the course; 10 students out of the 165 respondents volunteered to share their experiences in Psychology 101.

Phase Three: Qualitative Interviews

Student identification and probability calculations. Quantitative data only explains some of the variation among student outcomes, reaching a maximum of 63% in this study. In order to further examine the unmeasured variables within each student's

experience, probabilities for select students were first calculated using regression

coefficients outcomes and then followed by student interviews. In order to test the

accuracy of the regression models, coefficients from the logistic regression in block two

of Model Two and the profile of an average student (found in Table 9) were calculated

using the following equation: $\hat{Y}_i = p_i = 1/(1 + e^{-u}) = e^u/(1 + e^u)$.

Again, Model Two measures the predictive relationships between a student's

demographic and course performance variables, and the likelihood that they will pass the

course with a C or higher or receive a repeatable grade of C- or lower. The variable u in

the above equation stands for the regression equation. Each of the average student

characteristics and probability calculations are shown in Tables 9 and 10 below.

Table 9

Average Psychology 101 Student Profile Metrics

Variable	
Age	19
Grade Level	Sophomore
Citizenship	United States
First Language	English
California High School Graduate	Yes
Advanced Placement Credits Transferred	None
EOP Program Participant	No
Academic Probation History	No
Repeating Psychology 101	No

Note. n=5,447

Table 10

Average Student Success Probabilities Estimated from Regression Data

Variable		
Race/Ethnicity	Male Probability	Female Probability
American Indian	82%	83%
African American	86%	87%
Mexican American	86%	87%
Other Hispanic	86%	87%
Multiple Ethnicities	87%	88%
Asian	86%	87%
South East Asian	87%	88%
Pacific Islander	82%	83%
Filipino	86%	87%
Not Stated	86%	87%

Note. n=5,447

There are few differences among the probability of success of average students in each group, all with a greater than 80% likelihood of receiving a C grade or above. The average grade in the course among the sample population in Model Two (n= 5,447) was a C+, so these probabilities are consistent with the data. Using these outcomes and the study design, Mexican American, African American, and Filipino populations were still the largest populations (37% of all PSY 101 students) and those who were statistically less likely to be successful in the course. Further investigation of the predictive power of the regression model was conducted by calculating the probabilities of individual interview participants' success within the course.

There was a great deal of variability among individual student success probabilities, both confirming evidence and some unexpected outcomes shown in Table 11 below. For example, one student's demographic and performance variables (GPA, academic probation history) indicated a high probability of a non-repeatable grade (82%), but the student ultimately failed PSY 101. Another student whose profile estimated an extremely high probability of success (97%) received an expected A in the course. These two examples demonstrate that it cannot be assumed that the regression data will predict individual student grade outcomes. Therefore, students were interviewed to understand their individual course experiences and to extract additional unmeasured variables that potentially contributed to the students' statistical probability of success, compared to their actual course performance in Psychology 101.

Table 11

Study Participant Success Probabilities Estimated from Regression Data

Interview Participant	Probability of Receiving a Non-Repeatable Grade
Naomi	72% (final grade was a B)
Samuel	75% (final grade was a C)
Matthew	82% (final grade was an F)
Hunter	97% (final grade was an A)
Daryn	3% (final grade was an F)

Student interview participants. Student interviews were solicited from the same audience who took the questionnaire. The final question on the survey asked if the student would be interested in participating in an interview to share their individual experiences in the course. Ten students responded to the call and nine of them identified as Mexican American on their SDSU admission applications.

Since Mexican American students were the overwhelming response group, the selection process within the random stratified sample began with the identification of two Mexican American men who passed the class and two who received repeatable grades in the class (C- or below). These four students were selected for interviews based upon their overall performance in PSY 101 and because their race and gender were consistent with two of the most consistently significant demographic variables throughout the three regression models. A Mexican American woman was also selected at random from the remaining group of student interview volunteers to further explore some of the emergent themes within race.

Interview participant characteristics. Although responses from the five students who participated in the interviews are not generalizable to the entire population of class takers, they had similar characteristics to those who received and responded to the questionnaire. Students who provided interview data were freshman and sophomores, all

19 years of age, and with a slightly lower (2.55) grade point average compared to the population. All of the students originated from California high schools, and every student had a history of one or more blended learning course on their record. All but one of the students were eligible for financial aid, and one student was an Equal Opportunity Program (EOP) participant. The students all commute to campus from their family homes with the exception of one who resides on campus and is a member of the Honors Program.

Table 12

Study Participant Profiles

Student	Age	Class Year	Fin. Aid	EOP	GPA	PSY 101 Grade	CA High School
Naomi	19	Sophomore	Yes	Yes	2.04	B	Yes
Matthew	19	Sophomore	No	No	2.8	F	Yes
Samuel	19	Freshman	Yes	No	2.5	C	Yes
Hunter	19	Sophomore	Yes	No	3.94	A	Yes
Daryn	19	Freshman	Yes	No	1.45	F	Yes

Interview coding and analysis. The semi-structured interview design allowed flexibility to ask questions, delve deeper into key topics, and for the students to have space to share their experiences. Each student told his or her story, and the interview questions served as a guide that kept the discussion focused upon the academic experience. After reviewing the interview transcripts, the researcher used a holistic coding method to begin the analysis of themes (Saldaña, 2013). Eleven codes were extracted from the five interviews. These codes were identified as helpful in understanding how the probability of these students' success differed from their final grade in the course.

Phase three results. Student interviews helped address some of the explanatory gaps in the quantitative outcomes. Recall that this study was designed to learn whether there were predictive relationships between student demographic data and course performance and why those relationships may exist. In some cases the student interviews supported the quantitative data and in some they did not. These are reported below. The interviews introduced a number of unmeasured variables that students believe affected their performance in Psychology 101. They include financial crises, prolonged illness, and changing academic majors. The difference in the students' final grades was due in part to the control that they chose to take over the situation. From the interviews, agency was the unmeasured variable that separated the students who were not successful from those who were.

In order to keep the themes within the context of the personal stories that surround them, the first section reports on each individual interview. This report is followed by an explicit account of each theme, and the confirming or disconfirming evidence between the qualitative and quantitative data findings and how the student's management of the circumstances affected the student's performance in the class. The five students' stories included the following characteristics: student agency, study habits, student motivation, student course of study, perceptions of timesavings by taking a blended learning course, course expectations, class delivery preferences, personal challenges, Mexican American heritage and first generation college student status, social class, and community.

Naomi [2]. In some cases the student interviews supported the quantitative findings and in some cases they did not. Naomi for example, was successful in the course, but

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[2] All students' names have been changed.

according to the probability estimation derived from the regression analysis, there was only a 72% chance that she would receive a C or higher. She possessed a number of characteristics that suggested that she would not be successful in the class (Equal Opportunity Program participation, citizenship status, race/ethnicity). These were in addition to challenges at home, which included family pressures and her decision to change majors while trying to graduate on time. Despite the obstacles, Naomi's study habits, class attendance and exam preparation contributed to her success, demonstrating that the agency she took up in Psychology 101 helped her overcome the predictive variables that indicated otherwise.

Naomi is a Mexican American woman who was born in Tijuana, Mexico and moved with her family to the United States when she was in the second grade. Her first language is Spanish, and she is the first member in her immediate family to go to college. She lives with her parents in Chula Vista and commutes to SDSU. Two of her cousins also attend the university, and Naomi is close with one of them. The two women have the same major and often take classes together.

Naomi studies at home and only comes to campus for classes. She is not involved with clubs or social groups, but she is close to her EOP counselor as an Equal Opportunity Program participant. She likes that she has access to tutoring services through the program, but does not use them. Naomi explained that she is determined to take advantage of her experiences at SDSU, and she recognizes that she is receiving money from the government to do so.

The calculated probability of Naomi's success in the course was lower than that of an average Mexican American woman who took Psychology 101. According to

Naomi's individual variables, there was a 72% chance that she would receive a grade of C or higher in the course, but this was 15% lower than the average Mexican American, female student's probability of 87%. Ultimately she did receive a non-repeatable grade; she successfully earned a B in the course. Although Naomi experienced challenges while she was taking PSY 101, they did not necessarily align with the characteristics that the regression models predicted would pose a threat to her success.

In Naomi's case the following variables were negatively correlated with the likelihood that she would remain enrolled in the course and that she would receive a C or higher. Her Mexican American heritage, citizenship status, the number of units she earned since beginning school at SDSU, her age, her GPA (2.04), EOP eligibility, and the semester when she took the course were all variables that were statistically working against her projected success. Variables that bolstered her probability of receiving a passing grade were her advanced placement credits transferred from high school and her past history in a distance education or blended learning course.

The statistical factors were not the only obstacles in Naomi's path to success. Her interview added more detail to her difficult journey to succeed in the class. Naomi took Psychology 101 as a prerequisite for her social work major. However, her first course of study at SDSU was accounting. Her parents did not think a career in social work would be lucrative so they encouraged her to select something else. She struggled as an accounting major and is now on track to be a five-year graduate.

She retells the tension between her family's perceptions and experience and her own.

> …my parents don't understand that it has to be something that I'm going to be comfortable, something I'm going to like. And I get a lot of negative perspective from that. Obviously they support me but it's been tough on them. And it's tough on me from their part because they've never experienced the college, university life. And my mom actually went up to 7th grade and my dad up to 9th grade, so their education levels are very low as well.

She reports that her first year was difficult as she tried to manage the stress of not knowing what she was going to do next.

Naomi described how these events and other "stuff at home" affected her blended learning class experience. When she attended the live psychology class lectures she would be present. She sat in the front row and paid attention to the lessons. But when she was watching the lectures online, she recognized that distractions took her attention away from the class.

Naomi did not know Psychology 101 was a blended learning course when she registered, but she embraced the course format as something new. She liked the idea of attending lecture one day a week and not to be "forced" to watch the other lecture on a specific day. Instead she liked the idea that she could watch the lecture when she had the time. She would generally watch the lectures at school between her classes, but sometimes she would watch the lecture right before the live class lecture. Her preference overall was to attend the live lectures because she experienced fewer distractions in that space.

When Naomi studies for tests she makes flashcards, which she says she loves. She used the class PowerPoint presentations to inform her studies. She used the textbook for vocabulary terms but focused her attention on the class lectures. She talks about her cousin who was not successful in the course. The cousin failed the class when she and

Naomi took it together, and she retook it with success the second time. Naomi clarified that her cousin was really interested in the class, but ultimately she was not successful because she didn't put effort into studying.

The piece that gave Naomi a sense of community in class was the use of clickers. She shares her thoughts on feeling like clickers included her in the class discussion.

> I liked the clicker because it makes me be actually part, it makes me feel…obviously I'm in the class but it makes me feel more part of it. Because every question would come up and I would feel part of the…since it's such a big class I would feel part of the conversation because my vote would be there on whatever answer it was… Yeah. That made me feel part of the class community, the clicker.

At the end of the interview Naomi returns to the topic of her major. She says that she cannot take classes that she is ready to take to begin her social work major because they are not offered until the fall semester and that the classes must be taken in order. Her frustration comes from being unable to finish in four years because she took accounting classes as soon as she began school.

Naomi says her parents do not understand why she goes to school five days a week and her cousin only attends four days. They ask her if she needs "more learning" than her cousin. Similarly they cannot understand why switching majors takes an additional year of study. Naomi pushes this aside and takes a positive stance toward the future. When asked if she has any advice to share with other Psychology 101 students, she sums up her experiences by recommending that students try to remain motivated, "and think of the future rather than just the moment."

The quantitative variables that were working against Naomi were only compounded by the circumstances she described in her interview. So how can her course success be accounted for? First, even though there were a number of inverse

relationships between Naomi's profile and predicted success in the course, none of the coefficients in the quantitative models were strong enough to create an overwhelming likelihood that she would fail the class. Second, she took a number of actions that improved her chances of success. She employed a number of study skills that were not measured in the quantitative portion of this research but were identified through the interview as likely beneficial to her performance. For example, she made flashcards to study, attended lectures and exams, and sat in the front row where she knew she would focus on the class content – all actions that indicated that she was diligent about attending class and preparing for exams – two of the strongest predictors of student success in the quantitative phase of the study. Through her careful preparation, Naomi's case suggests that her agency, the individual actions that she took, prevailed over the variables that predicted she would not be successful.

Matthew. In Naomi's case, her sense of agency in taking control of the course requirements was a major contributor to her success in Psychology 101, despite variables that predicted otherwise. Matthew's case was on the opposite end of the spectrum, with circumstances that he could not anticipate or control. Matthew did not have a strong sense of urgency to repair his course performance in PSY 101, and the course just got away from him: first his attendance, then his assignments, and then he stopped taking the exams. He believes that you have to be a "certain kind of student" to be successful in a blended learning course, and he was not that student. Matthew had a high probability of success in the course, 10% higher than Naomi, and he did not pass the class. Matthew received an F despite an 82% estimated probability of succeeding in the course. So the

argument here is that despite the high predictability of his success, the actions he took up undermined a successful course outcome. So like Naomi – actions mattered.

According to the regression models, Matthew was well positioned for success. He had advanced placement units from high school, he took the course in the fall semester of 2014, which positively correlated with higher passing grades, and he had distance education or blended learning experience on his student record. These were all variables that positively correlated with student success in PSY 101. Matthew also possessed some variables that predicted a lower probability of success. He is Mexican American and male, his GPA was 2.80, which is not outstanding, but well above the 2.0 academic probation minimum at San Diego State. Unlike Naomi, however, Matthew did not study for class, and he did not attend on a regular basis. Matthew admitted that he was unable to focus and easily distracted. The unmeasured factors between Matthew's projected performance and his actual grade were better understood from his interview feedback.

Matthew shared that he received an F in the psychology course and only took the first two exams. He rarely attended class and that this was not the only course he failed that fall semester. He is majoring in Management Information Systems and enrolled in Psychology 101 to fulfill the general education requirement. He also enrolled because he is interested in psychology; he works in a pharmacy and wanted to learn more about how psychiatric medications work. He describes himself as never being a student organization person, even in high school, and he thinks that being involved with clubs on campus would cut into his time spent earning money at the pharmacy. Matthew was the only interview participant who was not eligible to receive financial aid.

During the interview Matthew stops to explain why he did not do well in his classes the semester he took Psychology 101. He was suffering from undiagnosed depression and anxiety and "every semester my performance seemed to get worse and worse and worse in school." He goes on to discuss his efforts to withdraw from the class, how he provided letters from his therapist and doctors but his requests were denied. In addition to his declining health Matthew was not even in the class he originally wanted to take. He preferred to take a traditional lecture-style course and was either unable or unmotivated to find an open section.

> So I originally wanted to take a standard class, but that particular semester that wasn't available. I couldn't take it…either I couldn't take it or it was booked. Because there was only one semester, or one section, and it was booked full. And so a lot of times the classes that I really want to take are not available, and so I'm going on to my second choice or my third choice or my fourth choice.

Later Matthew recalls that seats are always available for the blended learning sections of Psychology 101; the class never reaches capacity.

Like Naomi, time management and distractions were challenging for Matthew, but in Matthew's case they were harder to avoid. He preferred the live class sessions because it was easier for him to wake up in the morning and get dressed for class than it was to wake up and log on to watch the live online session. "I could be distracted with a hundred different things." He goes on to list online distractions, YouTube, Facebook, Instagram, Twitter, and explains that in live class lectures, which he was accustomed to from elementary through high school, the only thing you have to entertain yourself is the lecturer.

When Matthew stopped listening to the online sessions it also affected his in-class attendance and he did not take the last two exams.

> Because if you're missing out on, whether it's voluntary or just whatever, you're missing out on information. All of a sudden you're only getting half of the story, and so you just start to kind of feel not connected to the classes as much… But it would definitely impact my attendance, or even, as opposed to in-class, my ability to focus or my ability to understand what was being taught.

He attributes his poor performance to his lack of self-discipline and his inability to focus on the class when so many other events were occurring in his personal life, taking responsibility for his own performance outcomes.

When he did attend in-class lectures, Matthew kept to himself. He did not talk to other students because everyone sat in different seats in the lecture hall during each class. He also mentioned that only seeing classmates once a week made a difference in his ability to get to know people. When he was attending the online sessions Matthew logged in from home. He tried to make up the content he missed by reading the textbook and reviewing the PowerPoints, but he acknowledged that he was missing material that could only be accessed by attending class. He was also tempted by invitations to go out with friends and put studying off for another time.

Matthew avoids registering for courses in a blended learning format now, even the subjects he is interested in learning. He says he knows if he begins the course, at some point he will stop going online or stop paying attention. "You have to be a certain kind of student to really take advantage of the blended format." Matthew realizes that if he fails another blended learning course that it is "100% on me for failing." He sums up his class experience by advising future students to seriously consider the importance of the online class lectures, and to prioritize them as they would the in-class sessions.

Similar to the story of Naomi's blended learning course experience, it was the individual actions that Matthew took that resulted in poor course performance, despite the quantitative results that forecasted a high probability of success in the class.

Samuel. Although Samuel was motivated to succeed in the class, he was more affected by his need for community. He did not feel connected to any of the other students in the class in both the live sessions and within the online lectures. The probability calculation of Samuel's success in the course according to the weights of his individual variables from the regression analyses, reported that he had a 75% chance of receiving a C or higher in Psychology 101. This compared to the average Mexican American male student whose probability was 86%. Samuel received a C in the course. The variables in Samuel's profile that were known and most negatively correlated with his course grade were his race/ethnicity, age, and to some degree his 2.50 GPA. However, the variables that contributed to his overall performance in the course were not apparent in the quantitative data. For example, Samuel did not have a history of academic probation, but the qualitative data revealed that he had a medical emergency that required him to drop all of his classes, and when he was reinstated he followed a prescribed academic plan to ensure he was ready to return as a full time student.

Like Naomi, Samuel is also a commuter student from Chula Vista. He was born in Mexico City and his sister completed her degree in Administrative Business in Mexico. His parents did not attend college, but when he was asked if these details, his race and parents' education, influence his course experiences at SDSU, Samuel believes that the way students are accustomed to studying is the primary determinate of course performance. He goes on to discuss how he had grown accustom to high school

expectations for class success, which he now has come to realize are very different in college.

When he registered for Psychology 101 he describes adding the blended learning course to his schedule as "the freshman energy" full of optimism and determination. Samuel is very determined. He is majoring in Psychology and plans to add a minor in Biology. He aspires to go into the field of neuroscience, but his goals reach beyond earning a college degree. He believes with more education, there is a greater likelihood that he will break through social class barriers to pave the way for the next generation of his family. He sketched the hierarchy he was describing and shared that it takes a family generations upon generations to move from the lower and working class tiers to the next level. So even though Samuel does not believe that his family history influences his overall academic performance, he perceives the pursuit of higher education as a path toward the upward mobility he desires for his family.

Similar to Matthew, Samuel had to take time off from school because of an illness. He was hospitalized for a year and did not share the specifics of his condition. Samuel did not know about the university policy for leaves of absence, so he was put on a probationary plan when he returned to school. He was successful during this period and expects to graduate in two or two and half years. However, navigating and appealing university policies were raised in three of the interviews. In Matthew's case, his request to withdraw from PSY 101 was not granted; Samuel was reinstated to the university (this did not affect PSY 101), and Daryn, whose interview appears later in the chapter, successfully appealed an academic disqualification from SDSU. Although university policy is not directly connected to this research students' navigation and advocacy

through academic rules and regulations is further evidence of their agency to support their own success.

Time management was at the top of Samuel's list of reasons why the blended learning course was challenging for him. He believes that younger students, namely freshman, are not used to the "entirely new system" that blended learning presents.

> …so most of us come from high school where we're used to books and turning in assignments from class, not online. So when we're freshmen, it's a new, entirely new system. We're not used, we think we can go on with this hybrid class, like oh, it's going to be easy. We can take our time, we can do this, we can do that. It's a lie (laugh). What happens is we, most of us forget. That's about the closest thing I can get to, because we're not in that mindset that oh, tomorrow is class, we have to turn in this. Instead, it's we have three days to finish; I'll finish later.

He goes on to list class size, confidence to approach the professor, procrastination, and an investment in other tasks and activities as components of the new system.

Setting aside some of the larger concepts surrounding blended learning challenges Samuel explained that he had trouble interacting with other students in the class because hundreds of students would sit somewhere else each week. It's hard for him to approach people, and when he does it is because he says he has to get used to those around him. "So if you're a shy person and you keep to yourself, you don't have the opportunity to create those connections with other people." With this Samuel also pointed out that he thinks with so many people in the class there is much less accountability. Students can come and go as they please, and to turn in assignments or to skip them goes unnoticed in his opinion.

Samuel strongly dislikes online and blended learning courses. "Here at San Diego State, math was, it's complicated because online learning for me, it's not something that I enjoy. I hate it in fact." He shared that he feels as though his questions

are not answered and when he does receive a response he still may not know how to apply a concept. He takes online and blended learning courses when he has to complete a course over the summer or a required course like math, but will not take more than one class at a time.

Even though he disliked the course format, Samuel attended class, took the exams, watched the online lectures and completed Learning Curve online assignments. He enjoyed Dr. Laumakis as a professor, and he thought the videos and lessons were interesting, but he really enjoyed the case studies that appeared on the exams. He studies for his classes on campus because there are family distractions when he is at home.

When asked if he had anything else to add, Samuel offered that he looks for other courses for interesting content and discovered Coursera. Coursera is an online course platform primarily used to support free, massive open online courses (MOOCs). The platform supports more than 1,000 classes and has millions of registered users (Coursera, 2015). He thinks SDSU should implement a similar system. When asked why, he explained that he took a Coursera psychology course and was thrilled to see that discussion threads and the way people in the classes communicate with one another is transparent, with multiple contributors to questions, study tips and answers. It was in this online environment where Samuel felt close to other students, the teaching assistants, and the professor.

Samuel was motivated to perform well in PSY 101 on at least two levels. First, he believes that his college degree is linked to a greater social benefit for himself and his future family. He is also specifically interested in the field of Psychology; it is his major and a precursor to a much longer course of study toward a career in neuroscience.

Although he was successful in the course, it was community, or a lack thereof, that made Psychology 101 difficult for Samuel.

As someone who needs time to feel comfortable with other people in order to connect, Samuel missed this component in both the large, live lectures and in the online sessions, and even though he said he had a strong aversion to blended learning courses, he enjoyed the Coursera psychology class. This suggests that the way the SDSU blended learning courses are designed was troubling to Samuel, not necessarily the method of digital course delivery.

Although there were a number of measurable variables that predicted Samuel's probability for success in the course, the qualitative data demonstrate a number of unmeasured variables that were highly influential in Samuel's experience, including his sense of community, his health, and his interest and preference in other course delivery models. Of the five interview participants Samuel was most vocal about his experience and expectations in the course, but the relationships between his final grade and the data are not as clearly defined as in some of the other cases, including Hunter's story below.

Hunter. Hunter was the only student interview participant who lived on campus. He graduated from a California high school but he is not a San Diego native. As a member of the Honors Program, he lives with other Honors students on campus. Although he self-identified as Mexican American on his SDSU application, Hunter stated that he is one quarter Mexican, and although he feels disconnected from the culture he believes that his heritage shaped his and his family's professional and educational futures.

> I think a lot of the things that affect me now happened in the past. So for example though I'm not as 100% Mexican as my grandfather was he worked in certain occupations. He worked on water. He worked for the state in California, which I think affected my mother and the type of occupation she has. She's a hairdresser but fundamentally she's still wage laborer. So I think that in that regard, though I am not as Mexican as my grandfather is, I still think his position in society affected where I am now.

He went on to say that a lot of the students who came from working class parents did not go to school. Most of his friends went to community college and many dropped out and returned home.

Like Samuel, Hunter was motivated to be successful in his pursuit of a college degree, and in his interview he attributed his dedication to his desire to move up in the social hierarchy. Other than financial aid eligibility, this information is not available in the quantitative data. However, more interviews of first generation college students may reveal that they are exceptionally driven to succeed in school because of the social class implications and the impressions those students have of growing up in a working class household, looking forward to their chance to move up in the hierarchy.

Hunter applied to three University of California campuses and ultimately selected SDSU because of the Honors Program. He is the recipient of Pell Grant and Cal Grant scholarships, which pay for approximately 80% of his schooling. He took Psychology 101 in Spring 2013 and was able to recount each of his exam scores. He received an A in the course and attributes his success to paying close attention to the course lectures. Hunter's case is different in a number of ways, and one of them was that his academic performance was so high that any statistically demographic detractors, namely his race/ethnicity and gender, were inconsequential when the probability of his course success was estimated.

In the cases of Naomi, Samuel and Matthew, the estimated probability of their overall course performance was either inaccurate – in Matthew's case – or the percentage was close but not an unquestionable predictor of these students' final PSY 101 outcomes – in the cases of Naomi and Samuel. However, the estimated probability of these final two cases was an accurate predictor of the final grade outcomes for Hunter and Daryn. Hunter had a 97% estimated probability of receiving an A in Psychology 101.

In Hunter's case, he is a Mexican American male, and these two variables negatively correlate with successful student outcomes, but his GPA was high (3.94), and coupled with the high GPA coefficient in the model ($\beta = 3.81$) it surpassed the smaller, negative impact of race/ethnicity and gender. Hunter also had advanced placements credits and distance education/blended learning experience. Hunter's test scores were not factored into the probability estimation model but he also had near perfect test scores, including a perfect score on one of those exams. Unlike the other three cases, Hunter's hard work, scheduled study routine, and the community he had outside of the classroom accounted for some of the unmeasured factors that did not appear in the quantitative data, but did contribute to his unmistakable success in Psychology 101.

Hunter's sense of community reaches back to his own hometown where his sister's friend, recommended SDSU. From there he connected with the Honors community, the people he studies with, and those who took classes before him, and they share advice. He also has a number of mentor relationships with faculty.

> There are actually multiple people that took the Psych 101 class because I talked about it with other people as well. There's this video online that teaches you how to remember the parts of the brain. So a lot of my knowledge about doing well in the class came from other people.

Using the advice he received from other students and his own observations of the course, Hunter's plan to earn an A in the class included attending every face-to-face lecture, using his clicker to earn attendance points while he was there, and he also watched 90% of the online lectures, though he never woke up to watch them live. He would view the lectures in his dorm room. "It was hard though. It's a lot of self-regulation when you have the online stuff." In order to stay in a routine, Hunter made a schedule to view the online lectures, dedicating three-hour sessions to the psychology class two times a week. He recognized early on in the course that the time available to watch the lectures was open. "It was like, oh I'll do it whenever I need to…Okay, I'll push it to the next day. I'll push it to the next day."

When it came to reading for the course Hunter cannot remember whether he had the textbook. He said that after the first exam he calculated the time it would take to attend all of the lectures and verified that the test was written primarily from lecture materials. He then compared that time allocation to the amount of additional information and effort it would take to read the textbook. In his estimation it didn't add up, so Hunter spent his time attending lectures and studying the in-class materials, and used his remaining time for other classes and to read on his own.

Coming from a small town, Hunter noted that the library is tiny and the literature he was interested in reading was unavailable. When he came to SDSU he set out to read as much as he could. Here he commented on how he allocated his time to be able to invest in his reading.

> So if I could save my time from reading the somewhat boring psychology textbook to read, for example, like Erich Fromm was stuff I was interested in. So I was interested in psychology, it just wasn't necessarily the textbook psychology we had in class.

Hunter went on to talk about how taking courses online enabled him to complete two semesters of work in one semester in advance of a study abroad trip to Chile. He talks about an anthropology class that was completely online, and he hated it. He admits to cheating on the tests along with the rest of the class. He tempers the statement by sharing that Dr. Laumakis administered his exams in the classroom so students could not have their materials out for reference.

While Hunter is an example of a student who received an A in the class, his case also highlights a level of classroom acuity and study skills that were not revealed in the other interviews. Another factor that Hunter revealed in the interview that was not present in the other interviews was his deep sense of community at SDSU. It was through this community that he was able to get a sense of the PSY 101 workload and the most valuable course requirements including test points and attendance. His success in the class was due in large part to his strict study regimen, while his quantitatively predicted success in the class was a reflection of his existing academic performance. When Hunter applied the advice he received about the class to his already strong work ethic, the result was not only that he was successful in passing Psychology 101, but also earned a near-perfect grade.

Daryn. The semester Daryn took Psychology 101 he reported that he enjoyed attending the live lectures and changed his major from music to psychology. The quantitative data indicated that he would probably not be successful in the course with a 3% estimated probability of receiving a non-repeatable grade. However, many of the details in his interview indicated that he was an engaged and a productive student. Daryn was nearly disqualified from attending SDSU, but he attributes his academic recovery to

a different attitude and improved study habits. His interview helps explain why he was not successful in the class.

Daryn is a San Diego native and a commuter student. His mother was born in Mexico; she completed college, and was a teacher there. Now in the United States she cleans houses, and his dad is a cook. He identifies as a Mexican American but does not subscribe to what he calls the "victim mentality" in his community. He quotes what the victim mentality sounds like: "They arrest our people, the government takes our money." It did not surprise him to learn that statistically Mexican American students are at a disadvantage when it comes to success in Psychology 101 at SDSU.

Similar to Naomi, Daryn's family wants him to be successful and to earn money in his future career. He talked about growing up in poverty and how he views college as a way to move up socially. His mother talks about him becoming a doctor, and he says that he would like to earn a PhD, but Daryn originally came to SDSU because he is a musician, he plays the bass. His high school counselor suggested he apply to SDSU because music school was too expensive.

His sister attends SDSU and sometimes he sees her there, but he does not engage in any other student communities. He describes himself as shy, and he did not talk to any other students when he took Psychology 101. He also avoids approaching faculty at SDSU because he intimidated by the number of other students they serve, and to some extent their stature in the college community. However, he describes a faculty member from another local university as a friend. The two of them play music together, providing an opportunity for Daryn to ask him questions and get advice.

In Daryn's case, like Hunter's the estimated statistical probability of his overall course performance was accurate when it was compared to his final grade. The probability of Daryn receiving a C or higher in Psychology 101 was a mere 3%, and in this case he did receive an F in the class. Daryn's prior academic performance, coupled with his race/ethnicity and gender, yielded a low probability of success in Psychology 101. The exact causes of Daryn's poor performance are not known from the quantitative data; it is only apparent that he was not successful.

Again, the strongest predictors of student performance in the course were GPA, test scores and, in Daryn' case, attendance. Daryn was an at-risk student when he began the semester. He had a 1.45 GPA, coupled with his race/ethnicity, age, and academic probation status – all factors predicting a low probability for success.

To explain why his academic performance was so low in PSY 101, Daryn began by noting that after he received an F in the course he retook the class the next semester and received a B. When asked how he was able to turn his grade around so quickly, he pointed out that his study habits and school outlook changed. So, Daryn's case is an example of a student who increased his or her agency, he took control of his course performance, and in a short period of time also increased his final grade. The difference was not only in Daryn's outlook toward his own academic future, was also working through a personal struggle. It was early in his college career when his family came upon financial trouble, and he played music to earn money to help support the household. His grades suffered because he was working instead of concentrating on school. Soon after he changed his major to Psychology and made a tremendous grade recovery.

Daryn used course forgiveness to retake classes in an attempt to repair his 1.45 grade point average. After using 14 units of course forgiveness he was able to raise his GPA to 2.0. Similar to Matthew and Samuel, Daryn had to appeal to the university. In his case, it was to avoid being academically disqualified, which was supposed to happen based upon the number of semesters he was on academic probation. He worked directly with the Dean of the College of Sciences and was ultimately successful in his effort to remain enrolled at SDSU.

When he took PSY 101 Daryn saw the footnote on the registration stating that it was a blended learning course. He shared that he brought a high school mentality with him "to do everything last minute." He did not go to office hours, but he talks about liking the class and Dr. Laumakis' lectures. In fact, Daryn knew he was going to fail the class after the second test was administered; he never watched the online course sessions, but he still attended the live class lectures because he thought the information was interesting.

Daryn thinks the student-faculty ratio is much different than he was accustomed to in high school. He also thinks that traditional lectures, versus online lectures, have a different tone and that the examples are much more immediate. This is part of the reason he kept attending the class lectures after he knew he was not going to pass the course. When he did watch the online lectures he would go to the library or a Starbucks by his house. He lives at home with his parents.

If he could offer advice to other students it would be from his own past experience in the class. He would begin by asking, "Are you reading the book and watching the lectures?" And then he said they would go from there. He contends that

students will not be successful in the course unless they are reading and watching the lectures. At the end of the interview Daryn reflected upon his poor performance in the course. He said that if he knew that he was going to major in Psychology he would have never let himself fail the class.

In Daryn's case, the quantitative data support his final grade outcome, and the qualitative data help explain what happened during the semester when he failed the course. Similar to the other students, Daryn encountered socioeconomic troubles, navigating university policies, and specific to the course, he also had a sense that nobody really knew if he was present or absent. He was interested in the subject of psychology, but he was not able to stay on task or accountable to the tests, lectures – both live and virtual – or the studying that was required for success in Psychology 101.

Recurring themes. Eleven themes emerged from a holistic analysis of the five interviews: student agency, study habits, student motivation, the student's course of study, perceptions of timesavings by taking a blended learning course, course expectations/class delivery preferences, personal challenges, Mexican American heritage and first generation college student status, social class, and community. Only two of these variables appear in the quantitative data sets; there are race/ethnicity and financial aid programs and eligibility, which were included in the Enrollment Services data. Discreet race/ethnicity variables were reported in the Enrollment Services data, and social class proxies include financial aid eligibility and EOP participation. However, neither of these variables articulates the unmeasured factors included in the following themes.

Student agency. A recurring theme in each of the interviews is that of student agency. The actions these students took either supported or hindered their success in

Psychology 101. When Samuel and Matthew were sick they had to navigate SDSU

policies to be reinstated and further, they had to retake their courses or take a

predetermined set of classes to demonstrate proficiency. When Daryn was in the process

of being academically disqualified he had to take it upon himself to appeal to the

academic dean. Naomi knew her success in the course was attributed to her study efforts

while her cousin did not spend the same time studying and was not successful in the

class. Finally, Hunter attributes his success in PSY 101 to making sure he scheduled time

to watch the videos and to attend class.

   Study habits and student motivation. The kind of agency that students took up in

Psychology 101 was explained as the students described their study habits and

motivation. These two themes overlapped throughout the interviews. Each student

discussed the way the student approached preparation for Dr. Laumakis' class. Naomi

used flashcards, Matthew tried to keep up with homework assignments, and Hunter set a

study schedule to review the PowerPoint presentations. All of the students mentioned the

distractions and responsibility that accompanied the blended learning class, and some of

those distractions came from the online delivery of the class itself. Matthew shared that

he was easily distracted by a host of social media platforms that he would visit while

listing to class. Samuel talked about how he was susceptible to procrastination because

of the contrast of freedoms between high school and college studies.

   In each interview the students discussed additional unmeasured variables that

interfered with their studies and how they negotiated those situations. In some cases the

students ignored potential hazards to their progress and in other cases they were able to

detect negative behaviors before they began to adversely affect their grade in the class.

In all of the cases, students made decisions that were tied to their health and wellness, their socioeconomic status and goals, or to the pressure to succeed that they were experiencing at home. Oftentimes at least two of these scenarios were happening at the same time.

Student's course of study. All of the students mentioned their major and planned course of study as undergraduates and beyond, and many of them took PSY 101 as both a general education requirement and as a prerequisite for their respective majors. Although he changed majors after he took Psychology 101 the first time, Daryn reflects on his performance and shared that he would not have let himself fail the class if he knew that he would eventually change his music major to study psychology instead. This sentiment connects with psychology majors having a higher incentive to be successful in the course. These students see the relevance of the material in their academic career, whereas the first time he took the course Daryn was just trying to complete the class as a general education requirement.

Saving time. Time management was closely tied to students' study habits and how students assigned time to the class had an impact upon their final grades. Students thought taking Psychology 101 in a blended learning format would save them time. Matthew liked that he could sleep in and watch class lectures in his pajamas. Naomi didn't know PSY 101 was a blended learning class when she registered, but she was excited to learn that she only had to come to campus once a week to attend the lectures. Hunter's perception was that he had more time to go to the library and read about the subjects that interested him the most. Samuel perceived the blended learning format as a way to take his time in class. Finally, Daryn believed that viewing the video lectures was

more of an option than an integral piece contributing to successfully completing the class and spent his time outside of class playing music to earn money for his family.

As a result of this expectation, each student began the class with the assumption that the online sessions could be moved around to accommodate his or her busy schedules. This strategy impacted students' grades when they stopped watching the recorded lectures or when they played the lectures but turned their attention to another task at the same time. As students reflected upon the course format they discovered that attending both lectures each week was an integral component to being successful in the class.

Course expectations and class delivery preferences. This theme emerged in both the student interviews and the questionnaire, and it turns out that students prefer classroom lectures to the online sessions. Among the 168 survey respondents 78 selected the classroom lectures as their preferred class format. While the students who were interviewed initially expected the online sessions to be a timesaver and to add flexibility to their class schedules, they actually preferred to go to class. Most of them stated that the classroom environment had fewer distractions so they were forced to pay attention to the lesson. The students did not expect that the online lectures would take as much time to review and that they would hold the same amount or more value than the classroom sessions. In Matthew's case, missing the online sessions began a cycle of dismissing the class altogether.

Personal challenges. The interviews created a space for each student to share the story that, in their estimation, contributed to their overall performance in Psychology 101. In these five cases, the stories included financial hardship, family expectations, illness,

and extraordinary feats of recovery both physical and academic. Some of the students were explicit about their personal struggles while others hinted at obstacles they worked through and that they still encounter. Naomi was clear about her trouble as an accounting major while Samuel alluded to being hospitalized for a year. Each student case fills in some of the blanks when the predictive power of SPSS terminates. It was the way each student chose to address the student's specific challenge that impacted the final grade each received in the class.

Mexican American heritage and first generation college student status. While each student self-identified as Mexican American, the cultural nuances were less pronounced than the ways each linked his or her race/ethnicity to socioeconomic status. It was here where students discussed their experience of pressures to be successful in school, to earn money in their future careers and to break through socioeconomic barriers altogether. Although none of the students believed that his or her performance in PSY 101 was directly linked to his or her race, those who were first generation college students did attribute some of the challenges they have experienced at SDSU to not understanding the system, or more importantly, to their parents not understanding how the university works. For example, Naomi recounted that her parents do not understand how class scheduling works and why some students have more assigned class days than others.

Social class. Social class was unexpectedly connected to students' performance in the class. Most of the students who were interviewed were first generation college students who believe that earning a college degree will advance their social status, specifically Daryn and Samuel, who believe that earning a PhD will help them break

through social class barriers for their future family generations. Samuel, Hunter, Naomi and Daryn were all explicit about their family's roles within the working class and the expectations they put upon themselves or those of the family, to move beyond that societal tier.

Community. It would seem as though community is an important factor for course success among these five students. Most of the students mentioned the people they associated with on campus and all of them discussed the impersonal nature of the Psychology 101 lecture hall. However, Hunter was the only student interview participant who lived on campus and he was also involved within the Honors Program community. He was connected to people who took Psychology 101 before him, and he was an SDSU student partially because a neighbor and friend recommended the university.

Although the other students did not mention being involved within communities at SDSU, it was the absence of social ties that made community stand out as a relevant theme. Each was a local commuter student whose counselor advised him or her to apply to SDSU from his or her respective San Diego area high school. When the students were not at school they were at their family home nearby, mostly in the Chula Vista area, or they were at work. Other than a sibling or cousin, none of the students participated in clubs or campus organizations and none of them had close ties to friends on campus.

A crosstab analysis of the questionnaire data also alludes to a relationship between communication with other students in Psychology 101 and a sense of preparation and success in the course, although there are not enough observations to be sure. Of the 165 questionnaire respondents 92 selected "quizzes and exams" as a topic of conversation with other students in the class. Clickers were a distant second choice with

58 responses. Three of the five interview participants did not speak to other students in the class, and 23 of the questionnaire respondents said they also kept to themselves.

Findings around community indicate that there may be an opportunity to support students who take blended learning classes in ways outside of traditional clubs and on campus housing. For the most part these students are not traditional campus residents, and their interviews revealed that they do not spend time on campus if they do not have class or a required appointment. When they study it is at home or at a coffee shop. When the students do study on campus it is because they are waiting in between classes.

The students' impression of an impersonal class environment coupled with asynchronous recorded lectures may be an indication that PSY 101 requires more features that build community. The clickers, for example, made Naomi feel like she was part of a community even in the large lecture hall, and may signal a place to begin a deeper investigation into what community means to students and how if affects performance in PSY 101.

Summary of findings. The study confirmed that there were significant relationships between student demographic characteristics, Psychology 101 class retention and attrition, and final course grades. Some of the relationships were negative predictors and others were strong indicators of student course success. Further, the qualitative investigation into why these relationships exist revealed that students' agency and how they took control of their own learning despite challenges they faced while they were taking Psychology 101 was a strong determinate of their overall performance.

Research Question One, which asked to what extent student demographics can explain variation in the course withdrawal behavior of students enrolled in a blended

learning undergraduate psychology course at San Diego State University, was answered through the analysis of Model One and demonstrated that variables within race/ethnicity, age, gender, and socioeconomic status were negative predictors of student retention. Conversely, distance education/blended learning experience and citizenship were significant predictors of student persistence.

Although students who add and drop classes are creating "noise" within the registration process, potentially impacting the bottlenecked courses, it is not necessarily a negative activity. In fact, some of the data show that students who participate in the Equal Opportunity Program were more likely to drop the course. This could be attributed to the fact that they have received advising on SDSU policies and they are making informed decisions about their tuition dollars. On the other hand, students who remain in the class could be doing themselves a disservice if they are not prepared. Students with distance education and blended learning experience are much more likely to remain in the course, but in this model it did not predict their success and was not a significant variable in any of the other models.

Model Two was designed to address Research Question Two, to examine the extent to which student demographics and internal course performance data can explain variation in those students who received a passing grade versus students who received a repeatable grade of a C- or lower in Psychology 101. In this case, study findings also demonstrated a significant predictive relationship between many of the same variables from Model One. Race/ethnicity, gender, and age were again negative predictors of a students receiving grades of C or higher, along with the addition of a student performance variable, academic probation history. For Psychology 101 students who received grades

of C or higher, positive relationships were found between students who had high school advanced placement credits, and those whose attendance records (via clicker points) reflected their presence during the first two exams and the six classes in the first half of the course.

Model Three was designed to answer Research Question Three to determine if variance among passing grades in the course could be predicted by student demographic data. This investigation continued to support the findings that race/ethnicity, gender and, with the addition of student learning analytic data, exam performance negatively impact the subtle differences, for example, between an A- and a B+. Higher grades were connected with those students who transferred advanced placement credits from high school and those with consistent class attendance. There was also a positive relationship between the number of completed college units and performance.

When measures of individual student performance were added to student demographic data, the explanatory power of the models was substantially increased from 1% to 63% in one instance. The persistence of race/ethnicity findings prompted a deeper look into the 37% of variance within the personal experiences and course preferences of African American, Mexican American, and Filipino students, who were statistically more likely to drop, fail, and to receive lower grades in Psychology 101.

Although Mexican American students were less likely to be successful in Psychology 101, the qualitative findings do not support the generalized quantitative variable of race/ethnicity as the root cause of student performance. This was affirmed when students said that they did not think race was a factor that contributed to their course performance. Instead, race/ethnicity is nested in the cultural factors and social

class issues that were discussed in each of the five student meetings. As each student told his or her unique story, they brought up their own drive or their parents' desire for them to move out of the working class and to earn more money for themselves in the future. Further, four out of the five still live at home with their families and commute to campus, and all but one of the families qualify for financial aid. Since the quantitative data set did not include these nuances, the findings simply showed up as race/ethnicity and Equal Opportunity Program participation eligibility, which was a proxy for socioeconomic status.

Community, and the idea that students are buying or saving time by registering for a blended learning course were present in all of the interviews which suggests that students have expectations of blended learning classes before they begin taking the course. The community theme traces back to Community of Inquiry theory (CoI) theory, borrowed from distance education literature. One third of the CoI model is comprised of the "social presence" of students as an integral part of the learning experience. Students' assumption that they would save time by taking the course in a blended learning format was disproven both during and after the course for the students who were interviewed. If anything, students came away from the course realizing that finding the time to watch the online lectures is more demanding than attending lecture twice a week.

The findings from this study effectively answered each research question, and further, provided additional reports on both student trends and individual student experiences in Psychology 101. Although the estimated probabilities of students' final grades did not always accurately predict the outcomes, in three of the five cases (Matthew, Hunter and Daryn) the student interviews supported the final grades those

students received. In the remaining two instances (Naomi and Samuel) the qualitative data did not necessarily support or contradict the students' final grade. This may be due in part to both of these students receiving moderate grades, a B and C, in the course, instead of a high grade of an A or failing grade on the other side of the scale. The next chapter reports on interpretations of these outcomes, how they might be used in future studies, limitations, and the significance of conducting this research study.

CHAPTER FIVE

DISCUSSION

This final chapter begins with a discussion of the study's outcomes and how they manifest themselves within the context of the Psychology 101 course at San Diego State University, and the existing blended learning literature. Broadly, the findings provide confirming evidence that demographic variables such as race/ethnicity, citizenship, age, gender, institution of origin, socioeconomic status, and high school advanced placement test achievement are indeed predictors of student performance in the course. Each of these variables plays out in various ways throughout the study. While this research has policy and practice implications these, along with study limitations will be discussed. Finally, blended learning along with additional strategies intended to alleviate bottlenecks in the California State University system, such as intuitive electronic student advising systems and increased online course offerings, present a great deal of future research potential. Directions for future investigations based upon the findings of this study are discussed at the close of the chapter.

Discussion of Findings

This section will begin with a discussion of significant findings throughout each of the three phases of the study and their impact upon student performance in Psychology 101. Since the study included three separate phases, a synthesis of themes found within the quantitative and qualitative methods will be presented to demonstrate how some findings were only significant in some of the regression models, while others were significant in all of the models and were reiterated in the student interviews.

Phase one. Phase One was comprised of three distinct regression models that predicted student performance outcomes as a function of demographic variables and learning analytic data. The first and second models were binary logistic regressions; the first measured student retention and attrition and the second model measured students' who succeeded in the course and those who received a repeatable grade of a C- or lower. The third model, a linear regression, measured those students who passed the class with a C or higher and whether relationships existed between their demographic information and grade variance. Using the detailed findings from these models, several statistically significant variables appeared in more than one of the three models; these included: race/ethnicity, participation in the Compact for Success college preparatory program, grade point average, test performance, and gender.

Race/ethnicity. Race/ethnicity variables were significant predictors of student success throughout the quantitative portion of the study. Of course, it is unclear from this study if and how these findings are attributed to pre-existing achievement factors, since the groups who were statistically less successful in the course, specifically Mexican American and African American students, are also those cited as being less academically successful overall (The California Trust, 2010).

In Model One, students who identified as African American, Mexican American, South East Asian, and Filipino were statistically more likely to drop the course than the White student reference group, while in Model Two, students who self-identified as Other Hispanic, African American, Mexican American, and Filipino were statistically more likely to receive a C- or lower in Psychology 101. In Model Three, African

American and Mexican American students also appeared to be significantly less likely to receive higher grades than the other students in PSY 101.

The grade cutoffs used in the study were C and above (non-repeatable grade) and C- and below (repeatable grade) because SDSU policy allows students who receive grades below a C (minimum GPA for good standing is 2.0) to repeat the course and receive a higher grade to help repair their GPA. Students who reregister for courses they have already taken compound the bottlenecks that are already holding some first time class-takers back from registering for required courses.

Although the models only represented a part of the overall explanation as to why a student may not have performed well in the class, the literature cautions us that these variables cannot be taken singularly when observing retention and attrition behaviors.

> It is, for example, insufficient to include race and gender as two variables in a regression equation as a means of studying the racial and sexual character of dropout. Such inclusions do not capture the multitude of quantitative and qualitative differences in effect and interaction terms that race and gender produce in individual behavior (Tinto, 1982, p. 691).

As such, additional information was solicited from African American, Mexican American and Filipino students in Phases Two and Three in an effort to capture some of the differences that Tinto discusses.

As for the meaning of these race/ethnicity outcomes, there are scores of books and articles available on the topic of race/ethnicity and education, but none specifically discusses the phenomenon within a blended learning environment. Since the regression models only estimated the relationships between variables, it is hard to know how much and which facets of the complex process of passing or failing a class might have applied to this particular blended learning psychology class.

One potential explanation for the lower student performance measures found in this study may be attributed to an ongoing gap in educational outcomes. This "achievement gap" includes factors seen throughout the study such as socioeconomic status and first generation college student status (Harackiewicz, et al., 2014). Specifically, the "social-class achievement gap" can occur when neither of a student's parents received a four-year degree, which includes about 15-20% of American college students. These students are reported to be at a higher risk of dropping out of college or performing poorly, compared to continuing generation college students with one or both parents possessing a four-year degree.

The link between parental education levels and student performance occurs because a parent's highest level of education is often used as a proxy for socioeconomic status in studies of college student success. Students from households where neither parent holds a four-year degree are assumed to come from working class backgrounds (M. Jackman & R. Jackman, 1983). These students are considered to be at a disadvantage because of the likelihood that they attended a lower quality high school and had fewer resources for college preparation (Horvat, Weininger, & Lareau, 2003).

In response to the identification of an achievement gap at San Diego State, the university implemented programs to support student success and retention. Among these programs, the Compact for Success provides pre-college preparation for students in local high schools, and the Equal Opportunity Program (EOP) offers financial aid specifically for first-generation and low-income students (SDSU, 2012). The results of this study found that Compact for Success and Equal Opportunity Program participants were significantly more likely to drop Psychology 101 before the university deadline and

Compact for Success participants were also less likely to receive higher final grades in the class compared to nonparticipants.

Participation in Compact for Success. Compact for Success is a college preparatory program that guarantees admission to San Diego high school students who meet the program's prerequisites. Specifically, the program guarantees students from Sweetwater Union High School District – composed primarily of Hispanic families (61%), and where a majority of households (55%) have members whose highest institutional level of education is high school (National Demographics Corporation, 2014) – admission to SDSU if they meet five requirements. These requirements are: students must attend school within the Sweetwater Union High School District from seventh grade to their senior year; must maintain a 3.0 GPA; complete the A-G high school course curriculum requirements with a C grade or higher; satisfy the Entry Level English Placement (EPT) and Entry Level Math tests (ELM); and take the SAT or ACT entrance exams (SDSU, 2015d).

Compact for Success students in this study had negative coefficients in Models One and Three, β = -.266 and β = -.349 respectively. These relationships indicate that Compact Scholars were more likely to drop the course and to receive lower but still non-repeatable final grades of a C or higher. However, being a Compact Scholar was not a significant determinate for students who received repeatable grades of C- or lower in the course. This means that while students registered for the course and dropped it before the university deadline, many of the students who stayed in the class were ultimately successful and received a passing grade.

One possibility for this outcome is that the college preparatory advising that Compact Scholars received helped those students make timely decisions about adding and dropping classes from their course schedules. Another possibility is that the Compact for Success advising is not as effective, and students are registering for classes they are not ready to take. The Compact for Success participant variable was also significant in Model Three, which indicated that these students received lower grades than their peers who are not in the program. This may be another indication that Compact Scholars have a harder time in the class, but all of the students in the Model Three group received a grade of C or higher, keeping them above the minimum 2.0 GPA requirements and preventing them from repeating the course for a higher grade.

Grade point average and test performance. Incorporating student academic performance and learning analytic variables into the quantitative analysis was an important part of the study. These performance variables created an opportunity to identify potential areas for early course interventions to improve student success in PSY 101. Perhaps not surprisingly, grade point average (GPA) took most of the predictive power from the other variables in Models Two and Three, demonstrating that students who are already performing well in their classes were more likely to perform well in Psychology 101. Similar relationships existed between test scores and the students' final grades. There were some valuable findings, however, that came from adding learning analytic variables, test scores, and clicker points to Models Two and Three, despite the strong relationships that existed between the points students earn in the class and their final grades.

Attending classes – especially on exam days – was also a strong predictor of student success in the course. Clicker points were used as a proxy for in-class attendance. Coefficients for course attendance had an upward trajectory, beginning with the first class session in Model Two (β = .521) and increasing with nearly each subsequent live class session throughout the first half of the course. The same relationships occurred in Model Three, which measured the differences in final grades, although the coefficients were smaller. This indicates that students who attended the first six Psychology 101 classes during the first half of the semester were more likely to receive a passing grade than those who missed class. Further, students who attended the first six classes were also more likely to receive higher grades than those students who do not attend class. The strength of the attendance/course performance relationship became weaker after the sixth class indicating that variation in final grades decreased among students who continued to attend class beyond the first half of the course.

The most interesting relationship among the test performance variables was the strong positive and negative coefficients for test attendance and test performance. Students who attended Test One were significantly more likely to receive a grade of C or higher (β = 2.31). However, if the student scored in the lowest 25th percentile on Test One, they were also much more likely to receive a grade of C- or lower (β = -1.36). Test Two had the same characteristics but an even greater weight for each, (β = 3.11) and (β = -1.82). This finding has two potential implications for students. First, this presents an explanation, supported by data, to share with students so they are aware of the importance of attending the first and especially the second exams. Second, this finding also provides solid evidence that students should be aware that they need to score above 25 percent of

the class on the first two exams or they significantly increase their risk of receiving a C- or lower in the class.

Although these findings may sound like common sense, students look for trends in the class and ways to be successful. These data may help guide them as they plan how to use their time. This finding was reflected in the comments presented in the previous chapter from the interview with Hunter, who learned early on in the class that the lectures were the source for most of the information elicited on the exams. His class behavior reinforces the data; he attended the first six live class sessions, and he took notes, and scored well above the 25th percentile on the first two exams. In fact, Hunter scored in the 99th percentile on the exams.

One missing piece of this analysis was the frequency of students' online lecture attendance. Since this metric was not tracked on the Blackboard platform, it can only be inferred that online lecture attendance was also a predictor of student success and that students who regularly attended live class lectures were also attending the virtual lectures. This attendance trend was true for Hunter, but only moderately supported by Matthew and Daryn, who noted that although they attended the live lectures on a semi-regular basis they had little to no online course attendance. More research in this area, including tracking the trends among live and in-class lecture attendance throughout the semester, could point to additional predictive factors for overall student success.

Gender. Men were significantly more likely to drop Psychology 101 and less likely to receive a grade of C or higher. Not by a large margin in either case, but both findings were also found by the Public Policy Institute of California in their study of online course performance in California Community Colleges (CCC) (Johnson, & Mejia,

2014). In both studies, females both outnumbered males in the courses and within the overall institutional populations. Women were also more likely than men to take online community college classes, and ultimately outperformed them. Within this study of Psychology 101 students, the cause of the gendered performance gap is not clear and was not discussed within the context of the student questionnaire or the interviews.

A potential explanation for this gender disparity is that women in PSY 101 may have had a higher incentive to be successful in the course since there were substantially more women taking this course to fulfill a prerequisite requirement for their psychology major. A crosstab analysis of men and women who completed the class showed 800 of the 1,024 psychology majors were women (78%), more than three and a half times the number of male psychology majors. The major is the largest on campus and it is also impacted (San Diego State University Analytic Studies and Institutional Research, 2014). Students who pursue a psychology major at SDSU are required to complete seven prerequisite courses, receiving a grade of C or higher in each one, and Psychology 101 is among those courses (San Diego State University, 2015e).

Phase two. Phase Two included the administration of a six item questionnaire to 1,057 students who self-identified on their SDSU application as African American, Mexican American or Filipino. These were the students who were statistically more likely to drop, fail or receive lower grades than their peers in Psychology 101. This component of the research design served two purposes. The questionnaire data provided more detail surrounding the students' experiences in Psychology 101 and the information served to inform the interviews that followed the questionnaire analysis. The interview

questions centered on students' motivation, communication, and preparation experiences in the course.

The main findings from the student questionnaire indicate that a majority of the student respondents believed that taking Psychology 101 in a blended learning format would be more convenient for them. In response to the question, "What factor or factors motivated you to enroll in Psychology 101 as a blended learning/hybrid (part online, part classroom) course?" 47% of the students responded to this question stating that it was convenient to attend online and/or they liked attending in class one day and online the other day.

Students were then asked whether they felt prepared to take Psychology 101 in a blended learning (hybrid) format, and 53% of the student respondents felt unprepared or only somewhat prepared to take Psychology 101 as a blended course. Of these students more than half of the respondents overlapped with those who also liked coming to class one day and attending online on the other day. This means that the same students who did not feel completely prepared to take Psychology 101 in a blended learning format were also attracted to the convenience of taking the course in that format. This finding could present a problem when looking at blended learning courses through a student success lens. In other words, if students do not feel prepared to take the course in a blended learning format, why are they still enrolling in the course and what can the university do to help them prepare for this kind of format?

Some students reported that Psychology 101 was the only course that was available at the time when they registered. There is a possibility that students who do not feel prepared to take a blended learning course are being directed to enroll in the blended

Psychology 101 because they need to fulfill the general education requirement and that class is the only option to stay on track with their studies. Matthew alluded to this happening to him, saying that he was pretty sure there were no other courses available when he registered for PSY 101. He went on to say that there are always seats available for that particular psychology class. He could see hundreds of open seats when he went online to register. Matthew registered for the course anyway, and was not ultimately successful.

It is not clear from the questionnaire whether students who preferred the convenience of a blended learning course were more successful in passing the class, but the quantitative data showed that students who have prior distance education/blended learning history were more likely to remain in the class. More research is necessary to make a determination regarding whether students who feel comfortable taking a blended learning course are successful, or if feeling prepared for the format misleads students who think they are also ready for the course content.

Phase three. The quantitative work in the study provided generalizable information to begin understanding the profile of a student who is likely to be successful in Psychology 101. For example, the profile of such a student would be a White woman in her early 20s whose institution of origin was a high school outside of California and who transferred advanced placement credits to SDSU. Additionally, she would not participate in the Equal Opportunity Program or Compact for Success, would also have a mid-to-high grade point average, and at least one distance education/blended learning course on her transcript. However, it is not reasonable to assume that these findings

directly apply to all students since students are unique and so are their circumstances. This is why the final phase of the study was imperative.

Interviews with five of the Psychology 101 students produced 11 themes that helped explain why some of the students were successful in the course and some were not. There was an overarching theme of student agency that emerged throughout the interviews that helps to account for course outcomes specifically, it was the actions that students took over the circumstances they faced in the course which included students' study habits and attending classes both live and online. Outcomes were also influenced by students' motivation, their academic major, the perceptions they held regarding time requirements of a blended learning course, course expectations, class delivery preferences, personal challenges, their background including the combination of Mexican American heritage and being a first generation college student, social class, and the students' involvement or need for a community on campus.

The study began with a quantitative validation of the variables that predicted student performance. From that point, the student questionnaire was used to help tease out some deeper understanding of students' opinions about the course. Finally, the qualitative phase of the study explained why each student who was interviewed was or was not successful in the course and the extent to which the quantitative findings supported or contradicted that student's final grade. The themes that came from the interviews provided detailed accounts of the challenges students encountered when they took Psychology 101, in particular their agency or the actions and control that they took over their unique situations, made a difference in their individual final grade outcomes.

Many of the themes were closely related but students' perception of the timesavings by taking a blended learning course, their social class, and the community a student had in class or outside of class for studying and support, were most dominant throughout each of the interviews. Although these are three different themes, student agency was an overarching theme and connected to the ways student actions in these situations supported or undermined their success in Psychology 101. For example, timesavings were handled in one of two ways. First, all of the students who were interviewed assumed that they would save time by not being required to attend two live class lectures each week. It was the students who recognized that self-regulation and the need to stay on top of the recorded lectures was important not only for the content, but also as a connection to their performance and engagement in the live lecture were more successful in the class.

Student agency. As mentioned above student agency, or the control students chose to take or relinquish, during Psychology 101 was a consistent theme throughout the interviews and it became a key factor in many of the other themes, specifically when students were faced with personal challenges and managing their study habits. When Samuel and Matthew recounted how they battled health matters; one was able to attend classes, take notes and pass the class with a C; the other man was not able to generate the energy or the will to continue attending classes and received an F in PSY 101. Despite having her own obstacles with family and her academic major decisions, it was the agency Naomi took up by maintaining consistent study habits, continuing to attend classes, and studying for exams that made the difference between her predicted 72%

chance of receiving a repeatable grade of C or higher in Psychology 101, and the B grade that she earned.

Timesavings. Each student who was interviewed held the belief that blended learning classes would allow him or her to make more time for other priorities. Although blended learning environments vary from class to class, the Psychology 101 course at SDSU required students to attend live lecture once per week and view a live or recorded lecture for the other class session. The five students all discussed how they thought they would be able to fit more into their schedules by taking a blended learning course, dedicating what would be time spent in class instead to work, friends, or other classes.

In each instance, participants reflected on how this assumption and their behaviors impacted their course experience, and all realized that it was more difficult to focus on the online course lectures because other factors continually distracted them from their work. The students who were most negatively impacted by their inability to manage time in the course were the same two (Daryn and Matthew) who stopped watching the online sessions entirely, to instead direct their attention to activities outside of the course.

Daryn and Matthew both received an F in Psychology 101 and took responsibility for their respective grades. Looking back, each of them stated that he thought the online sessions were either optional or that he could wait to watch them later, and then turned his attention to other things. What is interesting about both of these students is that they still attended class. Matthew eventually stopped, but for the most part, the two men still got up in the morning, got dressed and came to lecture. Ultimately this means that even though they both thought the blended learning course format would save them time, the

only component they participated in were the live sessions, which took more time out of their day than attending the online sessions.

Each of the students also discussed the importance of keeping up with, and especially paying attention to, the online course sessions. Perhaps it was the way the class was configured, combined with some of the "high school mentality" that students noted they brought with them to college. Traditional classroom environments, as the students described from their experiences in high school, required students to be present in class and oftentimes, as in Psychology 101, attendance was taken and students received credit for being in class. Attendance was not taken in the online sessions, however, and there was no extrinsic reward for watching the online class lectures. Since live lecture attendance was a statistically significant predictor of student success, finding a way to track students' online attendance may increase both accountability and performance.

In addition to believing that taking a blended learning course would save students time, Matthew mentioned that he would multitask while he was watching the online lectures. He admits that although he was watching or listening to the lecture, the content was not of value to him because he was not paying attention; instead he was engaged in other activities on his computer. The assumption that a partially online course would save time was disastrous for Daryn and Matthew. Their decision to multitask proved detrimental to their success since both of these students received an F in the course. By the time the second test was administered the two students knew they were not going to be successful in the course. Both students repeated the same course to repair the failing

grades they received, and both made time to attend the live class sessions, online sessions, and the exams.

Social class. Although the quantitative phase of the study indicated that Equal Opportunity Program participation was negatively associated with student retention, financial need was not a significant predictor of student performance in Psychology 101. Issues related to social class were more complicated than just looking at participation in EOP as course grade predictor. It was important in student interviews to examine participants' familial and personal financial struggles, and especially how they experienced them at SDSU while taking Psychology 101. All but one of the students was eligible for financial aid, and at least two of the students were eligible for additional support through EOP and Pell grants. While these did not appear as significant variables in the quantitative data outcomes, the qualitative data demonstrated that students were acutely aware of their social status and goals. All but one student discussed how a college education would benefit themselves and their families.

Student attitudes toward education were positive and hopeful, according to the interview respondents. Independent of one another, two of the interview participants discussed their future education plans, and each of them mentioned that he thinks having a PhD will help him break through social class barriers. The students defined social class as having working class parents and families. One of the students, Samuel, drew a picture of a social hierarchy, pointing to each tier and sharing that multiple generations of family work and progress are required to move from one tier to the next. He plans on moving the needle so his future family will move out of the working class tier.

Daryn's story demonstrated how socioeconomic stressors negatively impacted his performance in Psychology 101. He needed to work late playing music to help support his family in a time of financial need. As a result, Daryn used his time outside of school for work and postponed watching the online class sessions. Eventually he stopped watching the online sessions entirely, and his live lecture class participation became sporadic. Daryn's family commitments and his own drive to complete his college degree, in this case, both had to do with his socioeconomic status, and in the end it cost him more money to persevere. In addition to retaking Psychology 101, Daryn repeated an additional six classes to correct his failing grade point average, costing him an a extra year of school time and more than a thousand dollars in tuition

Mexican American heritage and first generation college student status. The students who were interviewed did not believe that race was related to their academic performance, but the discussion surrounding social pressures from their families may be an environmental factor associated with both Mexican American heritage and first generation college student status. Hunter talked about his Mexican grandfather and both of his parents as working class, and how those roles have had an impact upon where he is now. The other interview participants also discussed their family's expectations.

Students stated that they feel the pressure coming from high family expectations to break through education and social barriers. Both Naomi's and Daryn's parents have expectations that they will become high-income earners, specifically an accountant and a doctor, respectively. At the same time, Naomi shared that her parents did not attend college and don't fully understand the discomfort she experienced as an accounting major or the time that is required for her to attend classes and to keep up with her studies. It is

not known if Daryn reprioritized his work and school responsibilities at the request of his family, but the combination of the two demands was too much for him to handle at one time and something had to give; eventually it was school. From the interviews it becomes apparent that in both Naomi and Daryn's cases high expectations at home were not supported with the resources the students needed to be successful the first time around. It was through their failure that the students took control of their own academic futures, changed their major course of study and began experiencing success in their classes.

Student community. One third of the Community of Inquiry Model (CoI) (discussed in Chapter Two) is comprised of student community and camaraderie, and was an important theme to investigate in this study (Garrison & Vaughn, 2008). Of the five interview participants, those who did not have a student community on campus, friends who they took classes with, or associations with clubs and organizations, did not excel in Psychology 101. Although student community was not measured in the regression analysis, questions about communication with other students appeared on the questionnaire. One question asked if students spoke to other people in class while they were attending Psychology 101, and if so, to share the topics they discussed with others.

Another interview question also asked about students' individual communities. The questionnaire responses showed that students who felt prepared to take Psychology 101 reported higher levels of communication with other students in the class than those who felt somewhat prepared or not at all prepared to take the class. These students discussed tests and quizzes, clickers, homework and some topics outside of class indicating that the community component was also germane to the course requirements.

However, these findings did not surface in the student interviews; instead, students described an isolated class experience with little to no community.

Students who shared their individual experiences in the interviews described a big lecture hall with hundreds of students who did not sit in the same place from week to week. In fact, three of the interview participants did not speak to any other students in the class. Naomi only spoke with her cousin, and Hunter had a community of Honors students in his life, both in and outside of class. Again, these were the experiences of just five class participants. However, it does make the point that the interviews gave students the opportunity to quantify their communications with other students in the class, while the questionnaire did not ask students how many people they spoke to each week. Therefore the questionnaire responses may be illustrating a richer community than actually existed in the class. In other words, respondents may only be describing communication with one friend, or they could be describing entire groups of students who spent time together in class each week.

Of the three students who did not speak to others, two were Matthew and Daryn, who did not pass the class. Part of this may be attributed to the fact that they did not attend class on a regular basis and were also withdrawn from the online content. Matthew mentioned having very little understanding of the live class lecture content after missing the online lectures. Daryn shared that he has a community of friends and that these were friends he went to high school with not students from SDSU. He spends time with them outside of school. It is not clear from the outcomes of this research whether student community was a predictor of success in the blended learning course, but

Community of Inquiry theory and responses to the questionnaire and interviews indicate that it is certainly an area for future research.

Synthesis of Key Findings

While the quantitative analysis provided statistically significant outcomes in response to the first three research questions, it was the synthesis of these findings with the qualitative data that explained why oftentimes, demographic variables alone are not the most accurate predictors of student course persistence, success or failure. The following are key findings in this study and revealed the following:

- Regression analysis revealed that student demographic data including race/ethnicity and socioeconomic status predict course outcomes in Psychology 101, to the extent that these variables suggested further qualitative investigation to explain why they were statistically significant.

- Qualitative data revealed a more complex and nuanced understanding of the quantitative outcomes and helped explain through the stories of five students why and how their performance was influenced or unchanged by their demographics and individual experiences in Psychology 101.

- Students' prior academic performance, specifically their grade point average, was a strong predictor of success in in Psychology 101. This, with class attendance and test scores provided the most explanatory power throughout the study, demonstrating that students who are already academically successful will likely remain successful and vice versa.

Overall, this explanatory study confirmed the existence of predictive relationships between a student's course performance and the student's demographic variables. Not

surprisingly, some variables were significant in just one model while others appeared throughout the study. For example, student Equal Opportunity Program (EOP) participants were significantly more likely to drop Psychology 101, but this was the only time EOP status was a significant predictive variable in the study. One explanation as to why EOP participation would negatively impact retention in Model One, but does not appear in the other two models, comes from the qualitative component of the study and is offered below.

In order for a student to qualify for EOP, the maximum income for a family of four is $46,500 (CSU Mentor, 2015). This indicates that students who are receiving government assistance, on average $900 per year, are more likely to drop the class before the final deadline. The hypothesis that students were carefully stewarding their government scholarship monies was supported by the comments Naomi made during her interview. She mentioned that she is receiving money from the government and she wants to make the most of it, which helped explain why a student who thinks the class is not a good fit might drop it before receiving a tuition penalty or a "W" on his or her transcript.

Although overcrowding in classes is a problem on California State University campuses, students are still adhering to the drop deadlines and in some cases conserving their own resources, including tuition money, or for those who are struggling academically, their overall grade point average. Students in Model Two are those who chose not to drop the course, some of whom were ultimately not successful and received a final grade of C- or lower. The study demonstrated which student characteristics predicted successful and unsuccessful course performance in Model Two, among them,

students who self-identified on their SDSU application as Mexican American. Questionnaires and interview data from some of the students indicated that a number of variables not used in the regressions influenced their student experiences and their course performance. An example of these circumstances informed by Phases Two and Three of the study is described here.

The results of the questionnaire suggest the possibility that students, who were not ready to take Psychology 101 or those who are not prepared to take a blended learning course, or both, still registered for the class. In Matthew's case, he did not want to take a blended learning class but the traditional classroom lectures were unavailable, or full as he recalls. He registered for the blended learning Psychology 101 class despite his reservations. When Matthew's depression became unmanageable he tried to withdraw from the course without it negatively impacting his grade. The university denied his request, and he continued a downward trend, ultimately receiving an F in the class.

One of the interesting findings from Matthew's case was that his calculated probability of receiving a non-repeatable grade in the class was 82%. The probability was estimated using his race/ethnicity, GPA, gender, age and other demographic variables from his student profile. As such, his demographic variables did not prove to be an accurate predictor of his final grade. The other factors in his life interfered with his performance, which to this point in his academic career had been productive. This outcome supported Matthew's story, that his SDSU experience began successfully and when his undiagnosed depression set in, he could not control his academic performance.

Attendance and student class preference were quantified in Models Two and Three and within the student questionnaire data. The themes were also mentioned in all

of the student interviews. It seems as though students prefer the idea of blended learning to the reality of taking the class in a blended learning format. Part of this dichotomy, according to students, is difficulty in exercising the discipline to attend both the online and live course lectures. The quantitative variables demonstrated the importance of attending the first six live class sessions, and while students preferred the live class sessions they still registered for the blended learning course and then demonstrated an aversion to the online class lectures. However, these particular students were being asked in the questionnaire to reflect upon their experience taking the blended learning class, so it is unknown how many of them continued to select blended learning course formats.

Interview participant Hunter contends that attending class is the only activity a student really needed to engage in to be successful in the course. He did not remember whether he had the course textbook, but he attended every class session and took copious notes from the lectures to study for the exams. He figured that only a few questions would be from material that was only in the textbook, so he allocated his time to the lectures alone. Hunter's probability of receiving an A in the course was 97% because his 3.94 grade point average combined with the high GPA coefficient ($\beta = 3.81$) overpowered any other negative coefficients in the equation. His final A grade affirmed the quantitative prediction.

When the probabilities were estimated from the coefficients in Model Two, which predicted the likelihood of a student repeatable/non-repeatable grade, an important factor was the student's GPA in the semester when the student began Psychology 101. Since Hunter's GPA was so high, his likelihood of passing the class was also high; similarly Daryn's GPA was low when he began PSY 101 (1.45), and his probability of passing the

class was also very low, 3%. These probabilities reinforced the notion that students who are already performing well in classes were likely to continue being successful.

Unexpected outcomes. The most unexpected finding was the discovery that some students were under the impression that taking a blended learning class would buy them time to dedicate towards other areas of their busy lives. Although this was unmeasured in the regression analyses, 54% of student questionnaire respondents selected, "It was convenient to go to class one day and attend online the other day." The finding was supported and further explained in the interviews. Each of the five students shared that he or she watched the online class sessions at different times, putting them off to engage in other activities. Eventually some of the students stopped participating in online sessions altogether. When this occurred, the students were also less likely to attend the live lectures. Investigating the relationship between online student engagement and traditional class lectures in a blended learning course format would be interesting future research to help understand how one potentially influences attendance behavior in the other.

Summary of Findings

Statistical and qualitative findings generated by the study were enumerated in Chapter Four, but the overall outcomes of this research revealed that there were significant relationships between student course performance outcomes and students' demographic variables in one blended learning psychology class instructed between Fall 2006 and Spring 2014.

The first research question asked, to what extent can student demographics explain variation in the course withdrawal behavior of students enrolled in a blended

learning undergraduate psychology course at San Diego State University? Specifically, can student demographics explain variation among those students who completed the course or dropped the course? Model One used a binary logistic regression to measure the retention and attrition behavior of 18,254 Psychology 101 students. The findings from Model One demonstrated that race/ethnicity, age, gender, and socioeconomic status were significant predictors of student attrition in Psychology 101. While the model only predicted 15% of the total variance, students with distance education/blended learning experience and those who were United States citizens were more like to remain in the course.

Of those students who remained in the class, the second research question asked, to what extent can student demographics and course performance data explain variation in those students who received a passing (non-repeatable) grade versus students who received a repeatable grade (C- or lower)? When students' course performance variables, academic record data, and demographic data were used to measure student success in the course, the strength of the binary regression model was substantially increased, explaining 49% of the total variance. Model Two demonstrated that many of the same variables – race/ethnicity, gender and age, and an additional variable, academic probation history – predicted that students were more likely to receive a grade of C- or lower in the course. Students who transferred high school advanced placement credits to San Diego State University, and those who attended the first two exams and the first six classes were more likely to receive a grade of C or higher.

The third research question focused upon the students who received non-repeatable grades in the course, asking specifically, among those who received a passing

grade in the course, to what extent can student demographics and internal course performance data explain variation in the final grades of students who took Psychology 101? Model Three had the most predictive power, 63%, and was designed to answer the third research question using a linear regression. The model demonstrated once again that race/ethnicity, gender and poor performance on the first two exams were predictors of lower, but non-repeatable grades of a C or higher. A positive relationship existed between higher test scores, advanced placement high school credits, attendance, and students who had more units at SDSU.

In other words, all three models indicated that although significant, the lowest level of predictive power came from student demographics alone. The explanatory power was increased when student performance variables including GPA and the number of earned course units were added to the model. The most predictive power came from the addition of attendance and test scores. Adding these learning analytics created a much more powerful Model Three. Administration of the course questionnaire and conducting student interviews to support or disconfirm the quantitative data helped explain the unmeasured variables surrounding the findings.

The most persistent statistically significant demographic variable findings were among African American and Mexican American students, who were more likely to drop, fail, and to receive lower grades in Psychology 101. The findings also revealed that although these outcomes are statistically significant, their contribution to the overall variance explained is low, in some cases a mere 1% (Model One, block one) of the reason why a student was or was not successful in the course. The addition of learning analytic variables to the models including student class attendance during the first half of the

semester and attendance and scores for tests one and two, substantially increased the explanatory power (63%), but this was largely driven by the strong correlations between course performance and final grade.

This study demonstrated the power of the evaluative data that resides in a blended learning pedagogy, allowing for an easier identification of potentially at-risk student groups and those who were ultimately successful in the course, all within a relatively short period of time. These findings allowed then, for a deeper discussion with students to address the final research question; what are the experiences of students whose demographic data most significantly explains performance in this blended learning psychology course? This question would help to uncover some of the factors that might help explain the 37% of students' experiences that were unmeasured by the regression models.

Research Question Four was answered with a combination of quantitative and qualitative methods. First, students within the three race/ethnicity groups who were statistically less likely to remain in the course, to pass with a non-repeatable grade, and/or receive higher grades than their peers completed questionnaires to share their experiences. Mexican American, African American and Filipino students who took the Psychology 101 course between Fall 2012 and Spring 2014, were asked about their motivation for enrolling in the course, how prepared they felt to take PSY 101, and whether they communicated with their classmates. Because of the anonymity of the responses, it was not known whether these respondents were successful in the class.

A majority of student respondents actually preferred the live classroom lectures to the online sessions, and most often spoke with other students about quizzes and exams.

When student responses to certain questions were combined using crosstab analysis, the outcomes pointed to potential performance hazards for students who did not feel prepared to take the class. For example, students who did not feel prepared to take the class were also attracted to the convenience of attending the live class session just one day per week. While it is not known if these same students were unsuccessful in the class, this does present an opportunity for future research.

Although significant predictive variables were available from the regression models, there were still unanswered questions about the individual experiences of students in the class, as reflected in the less than 100 percent predictive accuracy of the models. While each student's experience was different, eleven themes emerged after interviews were conducted with five Mexican American students, four men and one woman, to explain their individual experiences in Psychology 101. Two of the men and the young woman passed the course, and two of the men did not pass the course. A holistic analysis of the five interviews revealed the following themes which were discussed in detail in Chapter Four: student agency, study habits, student motivation, the student's course of study, perceptions of timesavings by taking a blended learning course, course expectations, class delivery preferences, personal challenges, Mexican American heritage and first generation college student status, social class, and community.

Blended Learning, Learning Analytics, and CSU System Research Contributions

First and foremost, this study was initiated because of the gaps in blended learning and learning analytics literature; as a result, researchers have called for more analyses of large-scale blended learning environments student learner outcomes. Since the California State University System is in the early phases of implementing blended

learning as a potential solution to alleviating bottlenecks on campuses, the time and place for this study were right. Creating a research design informed by the Community of Inquiry Model (Garrison & Vaughn, 2008) with the Learning Analytics Flow Model (Picciano, 2012), this study analyzed more than 18,000 student performance records in one CSU blended learning course, adding theoretical and practical implications to both blended learning and learning analytics.

As with any course, the faculty, textbooks, lesson plans, and even learning management systems change over time. Although the Psychology 101 course resources have been updated regularly since 2006, the textbook, assignments, faculty member, class sizes, and exams have all remained consistent over time. These consistencies made this large-scale analysis possible. Additionally, the discoveries around students' perception of timesavings and the research on student community in the class will contribute to the Community of Inquiry literature. The investigation of student preparation, motivation, and communication within the course may also pose potential tenets for new blended learning theory around student learning outcomes and engagement.

The second reason for initiating this research was inspired by the CSU's rapid implementation of blended learning in classrooms as a potential solution to alleviate bottleneck courses on campuses statewide. This research presents explanatory findings beginning with student performance in Psychology 101, but more importantly, the qualitative findings provide new information from students reporting on their experiences in the class. The research fits within the context of a current systemwide Student Success Initiative that includes grant incentives for faculty to redesign their courses with

technology, and blended learning solutions are among these redesigns. The limitations

for this study are found in the next section.

Limitations

With 190 final independent, dependent, interaction, and dummy codes

representing the personal and academic characteristics of 18,254 students, this was a

large study. While the statistical significance of the findings is solid, there are limitations

that accompany the research design and factors unique to the study and data.

Data provided by Enrollment Services contained student records for each student

interaction with Psychology 101 in the fall and spring semesters from Fall 2006 through

Spring 2014. These data may not have included potentially significant variables

including parent's highest level of education and student writing proficiency for example.

This methodological limitation was also noticed in the qualitative phase of the study

when unmeasured variables offered in the interviews proved to be important factors in a

students' course performance. Additionally, the data included student adds, drops and

course completions that resulted in students' final grades. Complete Blackboard

Learning Management System student performance data from Instructional Technology

Services were available from Spring 2010 through Spring 2014, ultimately limiting the

amount of student course performance data that were available for analysis. Therefore,

Enrollment Services data were used to analyze Research Question One and were

restricted to pair with the student records available within the Blackboard data in

Research Questions Two and Three. There were also randomly missing data for the

entire Spring 2012 semester and sections three and six in Fall 2010. These data were

eliminated before running the models to ensure the Enrollment Services data were not run against missing student records.

Second, the explanatory sequential research design for this study included student questionnaire data collection and interviews. While each phase of the study included the entire population or a subset of the total population, only 165 students responded to the questionnaire, and of those, five students were interviewed; these data are not representative of the entire Psychology 101 student population. Additionally, the student questionnaire had face validity, construct validity, and sampling validity, but was not designed or piloted as a reliable survey instrument.

Questionnaire recipients consisted of Mexican American, African American, and Filipino students who took Psychology 101 between Fall 2012 and Spring 2014. Mexican American student recipients outnumbered Filipino and African American students and also represented the largest participant group, creating an overrepresented set of respondents. Additionally, only a handful of responses were received from African American students. Further, Mexican American students were the only race/ethnicity group who participated in student interviews. These data are not generalizable, and interviews with students who were successful or unsuccessful in the psychology course may have presented a halo effect or distorted responses due to emotion, recall error, or anxiety. The optional nature of both the student questionnaire and the interview likely generated an unknown level of self-selection bias.

The third limitation of the study involved one member of the dissertation committee, Dr. Mark Laumakis, who serves as the faculty member for the Psychology 101 course in the study. Dr. Laumakis was present throughout the research, and although

he did not have contact with the data or the students who were surveyed or interviewed, his proximity to the study may have influenced the researcher in an unknown manner.

Finally, this research focused upon one blended learning psychology class and is not generalizable to other psychology classes or blended learning classes. This study was not designed to compare performance in the Psychology 101 course to that of a traditional face-to-face psychology course; therefore only generalizable findings within the Psychology 101 blended learning environment are reported. This may be one reason why it was difficult to discern some of the effects of race/ethnicity and student study habits. Implications for future research in these two areas are described in the next section.

Implications for Future Research and Practice

Blended learning research has largely concentrated on defining the discipline and has only recently moved into newer areas including best practices, learning analytics, and instructional design. This study works under the assumption that the Psychology 101 course was sufficiently defined as a blended learning course, thus enabling the research to move further into understanding learner outcomes. Having completed the scope of work for this study, this researcher believes the findings point toward additional areas for future analysis, policy, and practice.

Experimental design. Based upon the findings from this study it was discovered that it is difficult to separate traditional higher education course issues from those of the blended learning course environment, specifically, study skills and student achievement benefits or deficits within race/ethnicity categories. More research in these areas would potentially prevent historically underserved populations from experiencing similar or

additional challenges within a new learning environment. This research would likely call for an experimental design with a traditional Psychology 101 classroom course and a blended learning course. However, the size of the courses would need to be comparable, so the study would necessarily involve fewer participants.

Micro-level learning analytics. A second implication for future research is in the area of learning analytics. Since test data were highly correlated with students' final grade, it would be helpful to discover, extract, and measure different learning analytic measures associated with student success or poor performance. These would include micro-level measures of time on task, identification of student devices and off-task activities, peak study times, social media use for academic purposes, key stroke and question response time analysis during class assignments and online exams, and the impact of self directed and adaptive learning within a blended environment.

Although it was critical to the research design to use demographic variables for this study, the strength of the models was attributed primarily to the learning analytic data. The examples listed above represent learning analytic factors that are potentially correlated with a student's study habits and final grades. These data might hold significant explanatory power alongside clearer entry points for student success interventions.

Potential student success interventions may be designed in response to significant findings within a deeper exploration of learning analytic data, and certainly based upon the findings of this study. Focusing specifically upon community and the high value of participation and test scores in the first half of the class, interventions could include student community enhancements, increased incentives for online course participation,

and early alert systems for students, teaching assistants, counselors and faculty. Some of these strategies are already in place, but using the Blackboard Learning Management System data, generated in real time and coupled with the unmeasured variables that were analyzed in the qualitative phase of this study, may help refine the approaches.

For example, the students who were interviewed for the study each indicated that they watched the online course sessions at different times and in different locations. Only one student mentioned that the online sessions have a synchronous option. Using a synthesis of the quantitative and qualitative data, it seems there are three things taking place when students have trouble participating in the online sessions.

If students are not participating in synchronous sessions they are passively experiencing the class, which resulted in the students reporting that they multi-task or they are easily distracted from their work. Second, when students watch the recorded sessions there is no accountability, no attendance, no group work or discussion. This lack of accountability indicates that students do not feel a responsibility to attend the online sessions, which as was evidenced in the interviews, also impacted face-to-face course attendance and overall performance. The third occurrence, which may affect students' motivation and accountability to the online course sessions, is the absence of community when they are watching the asynchronous class. This is compounded when students enter the lecture hall to attend the live session and find what those who shared their course experiences characterized as a large, impersonal, student group.

Tracking peak hours to inform when students are most likely to be engaged in Learning Curve activities and recorded lecture sessions would facilitate the opportunity to reach students when they are online. More research could discover that students are

more likely to ask questions when they are watching the online courses sessions. If this were the case, perhaps opening a moderated (student, faculty or teaching assistant) online community during these peak student study hours would facilitate more class community and dialogue among those students who are otherwise attending the session independent of one another. This recommendation is also supported by Samuel's feedback about the open question and answer forums found in the Coursera classes he favored.

Course forgiveness policies and bottlenecks. University policy, though not the focus of this study, played a large role in the research. For example, SDSU's Course Forgiveness and Course Repeat policies enabled Daryn to recover from academic disqualification as a result of his efforts to appeal to the dean and to repair his poor GPA by retaking classes he failed for higher grades. In fact, at the beginning of the study, the description of the data provided by Enrollment Services included 18,254 students who had some interaction with Dr. Mark Laumakis' Psychology 101 class. Of those students, more than 3,000 duplicate entries indicated that students registered for the course more than once and many of them also repeated the course to receive a higher grade. This makes sense since PSY 101 is a highly repeatable course with 26% of this population receiving D, F, and W grades from 2006 through 2014. High demand for the course coupled with limited resources makes the bottleneck seem to be an inevitable circumstance with thousands of additional students repeating the course. In addition to moving forward with the blended learning model, San Diego State University should consider additional resources to support student success, and to provide alternative policy measures to reduce the influx of repeat students in Psychology 101.

Data management, integration and accessibility. This study required data sets from two different areas at SDSU. Enrollment Services data are not connected to Blackboard Learning Management data, and the process to combine these two data sets was more time consuming than some of the analysis. The CSU Student Success Dashboard is a new systemwide internal database designed to diagnose student performance issues and use predictive modeling to prepare and assess interventions on CSU campuses. Conducting research using this instrument and the potential power of its predictive capabilities could help support the learning analytic research taking place on an individual student level.

Course redesign pre and post analyses. A practical implication that may help the blended learning and the CSU communities would be to follow the courses pre and post-blended learning redesign. The course redesign effort already has a compendium of best practice portfolios for faculty to reference, but further, what are the pedagogical changes that a specific course undergoes when a faculty member restructures it as a blended learning environment for students? What are the constructs utilized in these instructional designs? This research demonstrates that the Community of Inquiry model does apply to blended learning practice by employing teaching, social, and cognitive presence, but building on the model and including learning analytics into evaluative measures will most likely improve upon the consistency and best practices in blended learning course design.

Big picture. Finally, does blended learning serve as an effective solution to alleviate bottlenecks and overcrowding on California State University campuses? If so, what are the future pedagogical and infrastructure trends for the changing university

environment? Will student commuter services be enhanced to include virtual student communities? How will this future impact faculty/student mentor relationships, and will these changes have an impact upon student affinity for their university? These questions only begin to articulate the research potential of student performance and learning analytics within the scope of blended learning in higher education.

Significance

With tremendous demand for California State University admission and the subsequent overcrowding, bottlenecks, and longer time-to-degree, it is understandable that alternatives to traditional classroom environments are being explored. This study provided empirical evidence of existing predictive relationships between demographic and performance variables in the Psychology 101 blended learning environment at San Diego State University, and then suggested a number of opportunities for student success interventions designed to improve student performance in the highly repeated course. Furthermore, questionnaire data and interviews indicated that a student's community, pre-dispositions regarding timesavings, and the impact of student agency and study skills are in some way connected to student success in the course but due to the limited sample size are not generalizable. This study does not advocate for or against the implementation of blended learning; instead it was designed to answer the call for research that may provide students with the support they need to be successful in the rapidly emerging higher education blended learning environment.

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APPENDIX A

2015 New Student Applications and Admissions Systemwide

2015 New Student Applications and Admissions Systemwide

CSU NEW STUDENTS (UNDUPLICATED) APPLICATIONS AND ADMISSIONS
SYSTEMWIDE, FALL 2014
ALL APPLICANTS
15-Apr-15

STUDENT LEVEL	APPLICATIONS RECEIVED	INCOMPLETE	DENIED	ADMITTED	ENROLLED
FIRST TIME FRESHMEN	209,558	25,428	32,892	151,073	64,254
UNDERGRAD TRANSFERS	117,999	14,720	18,767	84,395	51,524
POSTBACC/GRADUATES	66,316	12,380	20,258	33,411	20,690
TRANSITORY	3,891	18	2	3,870	4,952
UNKNOWN	313	64	226	0	0
TOTAL	398,077	52,610	72,145	272,749	141,420
PERCENT APPLICANTS	100	13.2	18.1	68.5	35.5
PERCENT ACCOMMODATED		13.2	18.1	68.6	35.6

APPENDIX B

The Sloan Consortium Quality Framework

The Sloan Consortium Quality Framework

Goal	Process/Practice	Sample Metric	Progress Indices
LEARNING EFFECTIVENESS			
The provider demonstrates that online learning outcomes meet or exceed institutional, industry, and/or community standards	Academic integrity and control reside with faculty in the same way as in traditional programs at the provider institution or organization	Faculty perception surveys or sampled interviews compare learning effectiveness in delivery modes Learner/graduate/employer focus groups or interviews measure learning gains	Faculty report online learning is equivalent or better Direct assessment of student learning is equivalent or better
SCALE (COST EFFECTIVENESS AND COMMITMENT)			
Providers continuously improve services while reducing costs	Providers demonstrate financial and technical commitment to online programs Tuition rates provide a fair return to the provider and best value to learners at the same time Tuition rates are equivalent or less than place-based tuition	Institutional and organizational stakeholders show support for participation in online education Effective practices are identified and implemented	The provider sustains the program, expands and scales upward as desired, strengthens and disseminates its mission and core values through online education
ACCESS			
All learners who wish to learn online can access learning in a wide array of programs & courses	Program entry processes inform learners of opportunities, and ensure that qualified, motivated learners have reliable access Integrated support services are available online to learners	Administrative and technical infrastructure provides access to all prospective and enrolled learners Quality metrics are used for information dissemination; learning resources delivery; and tutoring services	Qualitative indicators show continuous improvement in growth and effectiveness rates
FACULTY SATISFACTION			
Faculty are pleased with teaching online, citing appreciation and happiness	Processes ensure faculty participation in matters particular to online education (e.g. governance, intellectual property, and royalty sharing) Processes ensure adequate support for faculty in course preparation and course delivery	Repeat teaching of online courses by individual faculty indicates approval Addition of new faculty shows growing endorsement	Data from post-course surveys show continuous improvement: At least 90% of faculty believe the overall online teaching/learning experience is positive Willingness/desire to teach additional courses in the program: 80% positive
STUDENT SATISFACTION			
Students are pleased with their experiences in learning online, including interaction with instructors and peers, learning outcomes that match expectations, services, and orientation	Faculty/learner interaction is timely and substantive Adequate and fair systems assess course learning objectives, results are used for improving learning	Metrics show growing satisfaction via: . Surveys and/or interviews . Alumni surveys, referrals, testimonials . Outcomes measures . Focus groups . Faculty/Mentor/Advisor perceptions	Satisfaction measures show continuously increasing improvement Provider surveys, interviews, or other metrics show satisfaction levels are equivalent to or better than those of other delivery modes for the provider

APPENDIX C

SDSU Independent Variable Coding Specification

SDSU Independent Variable Coding Specification

Variable Category	Independent Variable	Code
Race/Ethnicity		
	American Indian	0 if other, 1 if American Indian
	African American	0 if other, 1 if African American
	Asian	0 if other, 1 if Asian
	Filipino	0 if other, 1 if Filipino
	Mexican American	0 if other, 1 if Mexican American
	Multiple Ethnicities	0 if other, 1 if Multiple Ethnicities
	Other Hispanic	0 if other, 1 if Other Hispanic
	Other/Not Stated	0 if other, 1 if Other/Not Stated
	Pacific Islander	0 if other, 1 if Pacific Islander
	Southeast Asian	0 if other, 1 if Southeast Asian
	White	0 if other, 1 if White
Gender		0 if Female, 1 if Male
Age		Continuous Variable
Citizenship and Language		
	US Citizen	0 if other, 1 if Citizen
	ESL	0 if other, 1 if English is Second Language
Socioeconomic Indicators		
	Financial Aid Eligibility	0 if other, 1 if Eligible
	Equal Opportunity Program	0 if other, 1 if EOP Enrolled
Matriculation Status		
	Freshman	0 if other, 1 if Freshman
	Sophomore	0 if other, 1 if Sophomore
	Junior	0 if other, 1 if Junior
	Senior	0 if other, 1 if Senior
Academic Standing		
	Total GPA	Continuous Variable
	Total Units Earned	Continuous Variable
	Academic Probation	0 if other, 1 if Probation History
Institution of Origin		
	CA Comm. College	0 if other, 1 if CA Community College
	Non-CA High School	0 if other, 1 if Non-CA High School
College Prep Indicators		
	Compact for Success – 1	0 if other, 1 if Compact for Success Scholar
	HS AP Credits (AP) – 1	0 of other, 1 if Advanced Placement Credits
Distance Ed/Blended Learning		
	Course History – 1	0 if other, 1 if Dist. Ed./Blended Learning
Psychology 101 Registration		
	2006-2007	0 if other, 1 if Fall 2006
		0 if other, 1 if Spring 2007
	2007-2008	0 if other, 1 if Fall 2007
		0 if other, 1 if Spring 2008
	2008-2009	0 if other, 1 if Fall 2008
		0 if other, 1 if Spring 2009
	2009-2010	0 if other, 1 if Fall 2009
		0 if other, 1 if Spring 2010
	2010-2011	0 if other, 1 if Fall 2010
		0 if other, 1 if Spring 2011
	2011-2012	0 if other, 1 if Fall 2011
		0 if other, 1 if Spring 2012
	2012-2013	0 if other, 1 if Fall 2012
		0 if other, 1 if Spring 2013
	2013-2014	0 if other, 1 if Fall 2013
		0 if other, 1 if Spring 2014
Course Exams		
	Test One	Continuous Variable
	Test Two	Continuous Variable
	Test Three	Continuous Variable
	Test Four	Continuous Variable
Clicker Points		
	Clicker 1	0 if other, 1 if Attended
	Clicker 2	0 if other, 1 if Attended
	Clicker 3	0 if other, 1 if Attended
	Clicker 4	0 if other, 1 if Attended
	Clicker 5	0 if other, 1 if Attended
	Clicker 6	0 if other, 1 if Attended

APPENDIX D

San Diego State University Grading Policies

San Diego State University Grading Policies (Page 1 of 3)

- Office of Violence against Women:
  United States Department of Justice
  http://www.ovw.usdoj.gov/
- Centers for Disease Control and Prevention:
  Intimate Partner Violence
  http://www.cdc.gov/ViolencePrevention/
  intimatepartnerviolence/index.html
- Defending Childhood, United States Department of Justice:
  http://www.justice.gov/defendingchildhood/
- Center for Community Solutions:
  4508 Mission Bay Drive
  San Diego, CA 92109
  1-888-DVLINKS (385-4657) 24-Hour Toll Free Crisisline
  http://www.ccssd.org

Immigration Requirements for Licensure

The Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (P.L. 104-193), also known as the Welfare Reform Act, includes provisions to eliminate eligibility for federal and state public benefits for certain categories of lawful immigrants as well as benefits for all illegal immigrants.

Students who will require a professional or commercial license provided by a local, state, or federal government agency in order to engage in an occupation for which the CSU may be training them must meet the immigration requirements of the Personal Responsibility and Work Opportunity Reconciliation Act to achieve licensure.

Numbering of Courses

Courses numbered 80 through 99 are nonbaccalaureate level and are not acceptable for a bachelor's degree; those numbered 100 through 299 are in the lower division (freshman and sophomore years); those numbered 300 through 499 are in the upper division (junior and senior years) and intended for undergraduates; those numbered 500 through 599 are in the upper division and are also acceptable for advanced degrees when taken by students admitted to graduate standing; those numbered 600 through 799 are graduate courses; and those numbered 800 through 899 are doctoral courses.

Courses numbered at the 900 level, except 997, are reserved for graduate courses in certain professional curricula as part of advanced certificate, credential, and licensure programs and are specifically intended for students admitted to the university with post-baccalaureate classified standing. Undergraduate students may enroll in these courses only if they are officially admitted to a blended or integrated program where undergraduate and credential coursework is included in the same program. Courses numbered at the 900 level are not applicable to other graduate programs.

Courses numbered 397 offered in regular sessions are professional advancement training or tutorial/discussion classes that accompany other credit courses and are not acceptable towards an undergraduate or graduate degree.

Courses numbered X-01 through X-79 and X-397 are Extension professional development units offered only through Extension to meet specific academic needs of community groups and are not acceptable toward an undergraduate or graduate degree.

Undergraduate Enrollment in 600-, 700-, and 800-Numbered Courses

1. Undergraduate students wishing to enroll in graduate level courses must file an undergraduate request form to enroll in graduate level courses prior to registering in any 600-, 700-, and 800- numbered courses.
2. Student must obtain permission of the instructor prior to submitting request form for approval.
3. Student must be a senior in good standing and have a B (3.0) GPA average in last 60 units.
4. Undergraduate enrollments may not cause the exclusion of a qualified graduate student in a graduate course.

NOTE: Coursework completed prior to earning a baccalaureate degree is not applicable toward any future graduate degree except under policy for concurrent Master's degree credit.

Grading System

Definition of Grades for Undergraduate Students

Grades and grade points per unit used in reporting are as follows: Grade of **A** (outstanding achievement; available only for the highest accomplishment), 4 points; **B** (praiseworthy performance; definitely above average), 3 points; **C** (average; awarded for satisfactory performance; the most common undergraduate grade), 2 points; **D** (minimally passing; less than the typical undergraduate achievement), 1 point; **F** (failing), 0 points; **RP** (report in progress), not counted in the grade point average; **W** (withdrawal), not counted in the grade point average; **AU** (audit), no credit earned and not counted in the grade point average; **Cr** (credit), signifying units earned, but not counted in the grade point average; **NC** (no credit), no credit earned and not counted in the grade point average; **I** (incomplete authorized), no credit earned and not counted in the grade point average until one calendar year has expired at which time it will be changed to an **IC** (Incomplete charged) and will count as an F for grade point average computation; **WU** (withdrawal unauthorized), will count as an F for grade point average computation.

Definition of Grades for Graduate Students

Grades and grade points per unit used in reporting are as follows: Grade of **A** (outstanding achievement; available for the highest accomplishment), 4 points; **B** (average; awarded for satisfactory performance), 3 points; **C** (minimally passing), 2 points; **D** (unacceptable for graduate credit; course must be repeated), 1 point; **F** (failing), 0 points; **RP** (report in progress), not counted in the grade point average; **W** (withdrawal), not counted in the grade point average; **AU** (audit), no credit earned and not counted in the grade point average; **Cr** (credit), signifying units earned, but not counted in the grade point average; **NC** (no credit), no credit earned and not counted in the grade point average; **I** (incomplete authorized), no credit earned and not counted in the grade point average until one calendar year has expired at which time it will be changed to an **IC** (incomplete charged) and will count as an F for grade point average computation; **WU** (withdrawal unauthorized), will count as an F for grade point average computation.

Plus/Minus Grading

A plus/minus grading system is utilized at San Diego State University. Plus/minus grading is not mandatory but is utilized at the discretion of the individual instructor. The grades of A+, F+ and F− are not issued. The decimal values of plus and/or minus grades are utilized in the calculation of grade point averages as follows:

A = 4.0	C+ = 2.3	D − = 0.7
A− = 3.7	C = 2.0	F = 0
B+ = 3.3	C− = 1.7	WU = 0
B = 3.0	D+ = 1.3	I = 0
B− = 2.7	D = 1.0	IC = 0

Faculty members use all grades from A through F to distinguish among levels of academic accomplishment. The grade for average undergraduate achievement is C.

Computation of Grade Point Average

To compute the grade point average, the total number of grade points earned is divided by the number of units attempted. Units earned with a Cr (Credit) are not included in the computation. A grade of I (incomplete authorized) is not counted in the grade point computation until one calendar year has expired, at which time it will be charged as an IC (incomplete charged) grade and will count as an F. The minimum GPA for a bachelor's degree is 2.0 (C); in other words, you must have earned at least twice as many grade points as units attempted.

Report in Progress Grade − RP

The RP symbol is used in connection with courses that extend beyond one academic term. It indicates that work is in progress and has been evaluated and found to be satisfactory to date, but that assignment of a precise grade must await completion of additional work. Work is to be completed within a stipulated time period not to exceed one year except for graduate thesis (799A) or dissertation (899). An additional exception shall be made for Research (797) in which time period is not to exceed two years. Graduate courses for which the RP symbol is appropriate are specifically designated in the departmental listings of the *Graduate Bulletin*.

San Diego State University Grading Policies (Page 2 of 3)

Candidates for graduation whose record carries a grade of RP will be graduated provided they are otherwise eligible for graduation. However, the RP cannot be made up after the degree has been granted. If students do not wish to be graduated with the grade of RP on their record, they must officially cancel their application for graduation.

Withdrawal Grade – W

The symbol "W" indicates that you were permitted to drop a course after the first 10 class days of the semester because of a verified serious and compelling reason, and you have obtained the signature of the instructor and the approval of the dean or designee of the college in which the class is located.

Dropping a class is not permitted after 11:59 p.m. on the 10th day from the first day of classes, except in cases such as accident or serious illness where the cause of dropping the class is due to circumstances clearly beyond your control, and the assignment of an incomplete is not practicable. All such requests must be accompanied by appropriate verification. Ordinarily, withdrawals in this category will involve total withdrawal from the university, except that credit, or an Incomplete, may be assigned for courses in which sufficient work has been completed to permit an evaluation to be made. Requests to withdraw under such circumstances must be signed by each instructor, who indicates your grade status in the class, and approved by the dean or designee of the college of your major.

After the last day of the semester, if you wish to change assigned grades to W grades you must request to withdraw from the full semester's work; no requests for individual classes will be accepted. Such requests may be granted only in verified cases such as accident or serious illness where the cause for substandard performance was due to circumstances clearly beyond your control. Only those retroactive changes from an assigned grade to a W which are approved by the instructor who assigned the original grade will be made, except that (a) the dean or designee of the college of your major may authorize the change of WU to W, and (b) department chairs shall act on behalf of instructors no longer affiliated with the university.

Auditing – AU

Enrollment as an auditor is subject to permission of the instructor, provided that enrollment in a course as an auditor shall be permitted only after students otherwise eligible to enroll on a credit basis have had an opportunity to do so. Auditors are subject to the same fee structure as credit students and regular class attendance is expected. Failure to meet required class attendance may result in an administrative drop of the course. Units taken for audit are not used in the calculation of enrollment status. To enroll as an auditor, obtain the *Change to Audit Grade* form from the Office of the Registrar. Obtain instructor approval and return the completed form by before 4 p.m. on the 10th day from the first day of classes to the Office of the Registrar. Once enrolled as an auditor, you may not change to credit status unless such a change is requested by 4 p.m. on the 10th day from the first day of classes.

Credit/No Credit – Cr/NC
(Undergraduate Student Option)

An undergraduate student may elect to be graded credit/no credit in particular courses, subject to the following conditions:

1. Upper division courses graded credit/no credit (Cr/NC), whether taken at this or at another institution, may not be used to satisfy requirements for your major or minor except for those courses identified in the course listing as graded Cr/NC.

2. Courses graded credit/no credit (Cr/NC) may not be used to satisfy I. Communication and Critical Thinking and II. Foundations of Learning A.4 Mathematics/Quantitative Reasoning sections of General Education.

3. No more than 15 units graded credit/no credit may be offered in satisfaction of the total units required in a bachelor's degree program, except that all units accepted as transfer credit from another institution at the time of your admission may be used. If 15 or more units graded credit/no credit are transferred, you may not use additional courses graded credit/no credit to satisfy total units required for a bachelor's degree. Exceptions to this rule will be made only if you are required to take an SDSU course on a credit/no credit basis.

4. Units for courses required for graduation which are offered for Cr/NC only will not be counted as part of the 15 elective units of Cr/NC allowed.

5. If for any reason (change of major or minor or transfer from another institution) upper division courses graded credit/ no credit are offered to satisfy requirements in the major, you may be required by the major department to pass competency examinations at an acceptable level or take prescribed alternate courses before being allowed to continue in the major.

6. Change in grading basis may be made through the SDSU WebPortal on or before the 15th day of instruction by 6:00 p.m. No changes in grading basis are permitted after that date.

7. A grade of Credit is awarded for work equivalent to all grades which earn 2.0 or more grade points (A through C). No Credit is awarded for work equivalent to all grades which earn less than 2.0 grade points (C – through F).

8. The only courses which may be repeated with a credit/no credit option are those in which you previously received a grade of No Credit. If a course previously taken for a grade is repeated for a grade of Credit, the original grade will continue to be used in computation of the grade point average.

NOTE: NC is not calculated in the grade point average at San Diego State University. However, some institutions, particularly for graduate admissions, calculate an NC as an F.

Incomplete Authorized Grade – I
(Undergraduate Student Option)

The symbol I (incomplete authorized) indicates that a portion of required coursework has not been completed and evaluated in the prescribed time period due to unforeseen, but fully justified, reasons and that there is still a possibility of earning credit. It is your responsibility to bring pertinent information to the instructor and to reach agreement on the means by which the remaining course requirements will be satisfied. The conditions for removal of the Incomplete shall be reduced to writing by the instructor and given to you with a copy placed on file with the department chair until the Incomplete is removed or the time limit for removal has passed. A final grade is assigned when the work agreed upon has been completed and evaluated. An Incomplete shall not be assigned when the only way you could make up the work would be to attend a major portion of the class when it is next offered. Contract forms for Incomplete grades are available at department offices or the Office of the Registrar website at http://www.sdsu.edu/registrar.

An Incomplete must be made up within one calendar year immediately following the end of the term in which it was assigned. This limitation prevails whether or not you maintain continuous enrollment. Failure to complete the assigned work within one calendar year will result in an Incomplete being converted to an IC symbol, which would become the final grade on the student's record at the end of the calendar year deadline. After one calendar year, the only way you may eliminate that grade from the grade point calculation is to repeat the course and file a petition for course forgiveness (see Repeated Courses below). In any case, because your record must provide an accurate and complete accounting of your academic history, the notation of Incomplete will remain on the record.

An incomplete may not be made up after you have graduated.

Incomplete Charged Grade – IC

The symbol IC (Incomplete charged) may be used when a student who received an authorized incomplete I has not completed the required coursework within the allowed time limit. The IC is posted to the record at the end of the one year time limit and is counted as a failing grade for grade point average and progress point computation.

Withdrawal Unauthorized Grade – WU

The symbol WU indicates that you enrolled in a course, did not withdraw from the course, but failed to complete course requirements. It is used when, in the opinion of the instructor, the number of completed assignments or course activities or both were insufficient to make possible a normal evaluation of academic performance. For purposes of grade point average computation, this symbol is equivalent to an F. If the student attended a portion of a course and then, after receiving failing grades, stopped attending without officially withdrawing, a final grade of F not WU should be assigned.

San Diego State University Grading Policies (Page 3 of 3)

Good Standing

Academic standing for undergraduate students at San Diego State University is determined by the grade point average a student earns in university areas. At the undergraduate level, good academic standing means that the student has an overall cumulative GPA and an SDSU cumulative GPA of 2.0 or better. (Students should note that in order to graduate, they also need a GPA of 2.0 in the major.)

Repeated Courses

Undergraduate students may repeat courses only if they earned grades lower than a C. A student who receives a grade of C- (fewer than 2.0 grade points per unit) or lower may request that the course repeat policy for grade forgiveness be applied to that course. *Students may request a maximum of 18 units for course forgiveness, with the constraint that no more than one course may be an upper division course. A course may be repeated once for course forgiveness. A 28 unit limit will be applied to repeated courses, including those in which course forgiveness has been approved.*

1. In the semester in which you are repeating a course for which you want an earlier grade forgiven, you must file a Course Forgiveness request via the SDSU WebPortal. While the original grade(s) will remain on your record, the grade earned in the repeat, whether higher or lower than the original grade, will be used in place of the earlier grade in the calculation of grade point averages.

2. The course forgiveness and course repeat policy applies only to repeats of the *same course* (same number, same title, and, for Experimental Topics courses, same subtitle). Exceptions will be made only in those cases where the course number changes and the change is documented in the *General Catalog*.

3. In some cases, admission to courses may have become restricted due to impaction, limitation by major code, enforcement of prerequisites, or sequence requirements (e.g., mathematics and foreign language). In those cases, you are prohibited from repeating those courses.

4. The only courses which may be repeated Credit/No Credit are those in which you previously received No Credit; if a course previously taken for a grade is repeated Credit/No Credit, the original grade will continue to be calculated in grade point averages. Repeating courses in which the original grade was No Credit (NC) does not require the filing of the Course Forgiveness request.

5. The course forgiveness policy may be extended to courses originally taken elsewhere and repeated at San Diego State University, in which case the original transfer grade will no longer be used in the calculation of the overall grade point average. However, the course forgiveness policy applies only to courses repeated at San Diego State University.

6. The course forgiveness policy applies to courses repeated at San Diego State University in summer terms and to courses repeated through Open University during the summer term, fall and/or spring semesters.

7. If courses with C- or lower grades are repeated without course forgiveness approval or in excess of course repeat limitations, all grades for those courses will be calculated in grade point averages. Units for a course will be counted only once toward graduation, regardless of the number of repeats.

8. Course forgiveness is only applicable to undergraduate students pursuing a first bachelor's degree.

9. Per University Senate policy, course forgiveness will not be granted if the Center for Student Rights and Responsibilities finds the student guilty of academic dishonesty in that particular course.

Assignment of Grades and Grade Appeals

Faculty have the right and responsibility to provide evaluation and timely assignment of appropriate grades. There is a presumption that grades assigned are correct. It is the responsibility of anyone appealing an assigned grade to demonstrate otherwise.

If you believe that an appropriate grade has not been assigned you should first seek to resolve the matter with the instructor of record. If the matter cannot be resolved informally, you may present the case to the appropriate campus entity, have it reviewed and, where justified,

receive a grade correction. It is your responsibility to attempt to resolve grade disputes in a timely manner, typically during the semester following the semester the questioned grade was received. If 12 or more months have elapsed since the grade was issued, or you have graduated, no grade change will be considered.

Dean's List

The Dean's List recognizes academic achievement within a single fall semester or spring semester. To be eligible for the Dean's List, students must be in good academic standing, matriculated, and have a grade point average of at least 3.50 based on a minimum of 12 units of credit for courses in which letter grades were assigned. The computation of grade points will be made six weeks after the end of the semester to include students who complete Incomplete grades promptly.

Students will be recognized by the dean of their respective college; undeclared, interdisciplinary studies in three departments, and liberal studies majors will be listed by the dean of undergraduate studies.

Graduation With Honors and Distinction

Graduation with honors is granted to undergraduate students who achieve high grade point averages. Excellence is recognized at three levels:

- *cum laude* (3.50-3.64)
- *magna cum laude* (3.65-3.79)
- *summa cum laude* (3.80-4.00)

For determination of eligibility, two grade point averages are computed; *both* must satisfy the minimum grade point average for appropriate honors designation. They are the GPA calculated on all units taken at this institution (a minimum of 24 graded units), and the overall (cumulative) grade point average (including both SDSU and transfer units).

Grades for the final semester's work are included in calculation of eligibility for graduation with honors. Students are tentatively designated as eligible for graduation with honors if both grade point averages meet required standards at the beginning of the fall semester for midyear graduates and at the end of the fall semester for May and summer term graduates. Notation of *cum laude, magna cum laude, or summa cum laude* on transcripts and diplomas is based on achievement when all courses for graduation are completed. Second bachelor's degree in nursing candidates are not eligible for graduation with honors.

Upon recommendation of their major department, students doing superior work in their major field may be graduated with distinction in that field. To qualify for Distinction in the Major, a student must have a minimum 3.50 grade point average in the major (upper division courses) by the beginning of the fall semester for midyear graduates and by the end of the fall semester for May and summer term graduates. Departments may set a higher GPA or additional criteria. Second bachelor's degree in nursing candidates are eligible for Distinction in the Major.

To be considered for computation of the major grade point average, grades for removal of Incomplete and all other grade changes must be received in the Office of the Registrar no later than the end of the fifth week of the semester in which the student plans to graduate. All changes for summer term graduates must be received by the end of the fifth week of the spring semester prior to graduation.

Final Examinations

No final examination shall be given to individual students before the regular time. If you find it impossible to take a final examination on the date scheduled you must make arrangements with the instructor to have an incomplete grade reported and must take the deferred final examination within the time allowed for making up incomplete grades.

Evaluation

An evaluation is a summary of college work completed and of requirements to be completed for a bachelor's degree. New transfer students will receive an evaluation prior to second semester registration. Transfer courses will be included, where applicable, to meet San Diego State University's degree requirements. Students admitted as freshmen will receive an evaluation at the end of the second semester of attendance. Continuing students may request updates to the evaluation at the Academic Advising Center, located in Student Services West, Room 1551 or on the SDSU WebPortal at http://www.sdsu.edu/portal.

APPENDIX E

Student Questionnaire Email and Instrument

Student Questionnaire Email and Instrument (Page 1 of 2)

Block 1

Thank you for taking the time to complete this quick survey about the Psychology 101 class you took between 2012 and 2014.

You are receiving this survey (6 multiple choice questions) because you were enrolled in Dr. Mark Laumakis' Psychology 101 course and your course performance and demographic characteristics have been identified as significant findings within the research I am conducting.

PLEASE NOTE: If you did not do well or pass the class, you are a really important part of this study, and your voice will help me make recommendations for future classes and student success.

Respectfully,
Maureen A. Guarcello
Volunteer Staff Researcher, SDSU Instructional Technology Services
Doctoral Candidate, University of San Diego

If you have any questions about this questionnaire, please feel free to contact me by email or phone:
Maureen Guarcello, mguarcello@mail.sdsu.edu, (562) 243-2036
or the Institutional Review Board at SDSU, (619) 594-6622

Default Question Block

What factor or factors motivated you to enroll in Psychology 101 as a blended learning/hybrid (part online, part classroom) course? (Please check all that apply.)

I liked the online option.

It was convenient to go to class one day and attend online the other day.

It was the only Psychology 101 course available.

It was the only class that fit my schedule.

I heard about it from a friend/classmate.

A friend/classmate was also taking the class.

I already took the class and was repeating it to earn a higher grade.

Other (Please explain)

What lecture format did you prefer when you took Psychology 101?

Classroom lectures

Online lectures

I preferred both classroom and online lectures equally.

I did not have a preference between the two lecture formats.

What did you talk about with other students in your Psychology 101 class? (Please check all that apply.)

Homework assignments

Student Questionnaire Email and Instrument (Page 2 of 2)

Quizzes and exams

☐ Attendence

☐ Online lectures

☐ In class lectures

☐ Clickers

☐ Technical support issues

☐ Study groups

☐ Topics outside of the class

☐ I did not talk with other students in Psychology 101.

☐ Other (Please explain)

[   ]

Setting aside your final grade in the course, did you feel prepared to take Psychology 101 in a blended learning (hybrid) format?

○ I felt completely prepared to take Psychology 101 in a blended learning format.

○ I felt somewhat prepared to take Psychology 101 in a blended learning format.

○ I did not feel prepared to take Psychology 101 in a blended learning format.

Did you receive a grade of C or higher in Psychology 101? (This includes receiving credit in the course.)

○ Yes

○ No

○ I took the class more than once and received more than one grade.

○ I don't remember.

This study looks at the experiences of students who took Psychology 101 in a blended learning format. Of course it is important to understand the experiences of those who passed Psychology 101 and those who did not do as well.

As such, would you be willing to volunteer 30 minutes of your time for a short interview so I can learn more about your experience in this class for my research? Your name and responses will be kept confidential and will in no way impact your academic record.

○ Yes, I am interested in sharing my Psychology 101 blended learning experience for this research study. (Please add your email address below and I will contact you directly.)

[   ]

○ No, I am not interested in being interviewed.

APPENDIX F

Institutional Review Board Approved Informed Consent

Institutional Review Board Approved Informed Consent (Page 1 of 2)

Sample Interview Consent Form

Research Title: Blended Learning and Bottlenecks: An Empirical Look at the Importance of Demographic and Performance Analytics

Principal Investigator: Maureen A. Guarcello
Email: mguarcello@mail.sdsu.edu
Phone: (562) 243-2036

Co-Principal Investigator (not present for interviews): Dr. Mark Laumakis
Email: mlaumakis@mail.sdsu.edu
Phone: (619) 594-1933

Dear Interview Participant,

I am a University of San Diego doctoral candidate and a San Diego State University Volunteer Staff Researcher conducting my dissertation research on the relationships between student demographic data and class performance in a blended learning course at SDSU. This study is important because SDSU is implementing blended learning (partially face-to-face and partially online) classes to continue providing quality education to students while accommodating the high student demand for classes. There is slim research on individual student experiences these blended learning environments, which is why this study is being conducted.

You have been selected to participate because you were enrolled in a blended learning Psychology 101 course with Dr. Mark Laumakis between Fall 2012 and Spring 2014. You also shared your interest in volunteering for an interview when you completed the online questionnaire for this study.

This research participation will entail a thirty-minute interview to learn about how students felt about the face-to-face and online lectures, the class community, and overall performance in the class. If you did not complete or pass the class, it is important that students, who withdrew from the class, took an incomplete, or received a repeatable grade of a C- or lower, are also represented in the study.

Participation is voluntary and if at any time you would like to stop the interview, you may do so without explanation. Your information will remain confidential which means that all research from this point forward will be separated from your identity. There are no risks to participating in this interview that are any greater than those encountered in everyday life.

There are no incentives to participate in this research, although your volunteer efforts will help inform future Psychology 101 blended learning courses at SDSU.
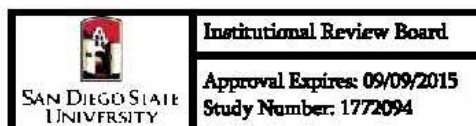
Institutional Review Board Approved Informed Consent (Page 2 of 2)

Participant's Agreement:

You are aware that your participation in this interview is voluntary. You understand the intent and purpose of this research. If, for any reason, at any time, you wish to stop the interview, you may do so without having to give an explanation.

The researcher has reviewed the individual and social benefits and risks of this project with me. You are aware the data will be used in a doctoral dissertation that will be publicly available at the University of San Diego. You have the right to review, comment on, and/or withdraw information after reviewing the interview transcript. The data gathered in this study are confidential with respect to your personal identity unless you specify otherwise.

If you have any questions, problems or concerns about this study, you are free to contact the researcher, Maureen Guarcello and the Institutional Review Board at SDSU, (619) 594-6622.

You have been offered a copy of this consent form that you may keep for your own reference.

You have read the above form and, with the understanding that you can withdraw at any time and for whatever reason.

You consent to participate in today's interview.

_____   _____
Participant's Signature   Date

_____
Interviewer's Signature

	Institutional Review Board
SAN DIEGO STATE UNIVERSITY	Approval Expires: 09/09/2015 Study Number: 1772094
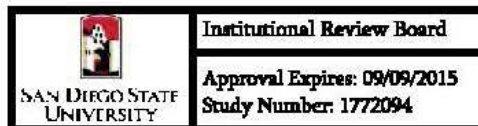
APPENDIX G

Institutional Review Board Approved Semi-Structured Interview Guide

Institutional Review Board Approved Semi-Structured Interview Guide

This is a list of the questions that will be asked of voluntary participants who took Psychology 101 with Dr. Mark Laumakis between Fall 2012 and Spring 2014. All consent and protocol documents have been approved. These interview questions are now finalized and were pledged to be appended to the IRB approved protocol when they were complete.

1. What did you think about taking Psychology 101 in a blended learning (partially online, partially in-class) format?

2. Did you feel as though Dr. Laumakis was available to answer questions or to help outside of class, even though there were many other students?

3. When you attended the course online and on campus, did you do things the same way? For example, always log on from the same location, or at the same time. Or did you sit in the same place or with similar groups of people when you attended class in person?

4. What was most interesting to you about the course? This could include anything that you experienced in class and/or online.

5. Do you have any questions for me?

APPENDIX H

San Diego State University Enrollment Services SIMS/R Data Codebook

Description of the Population: Matriculated undergraduate students who enrolled in Psychology 101 sections taught by Dr. Mark Laumakis between Fall 2006 and Spring 2014, excluding summer sections.

Code Category and Description

STU_ID: A unique number assigned by the campus

PERIOD: This is the period in which the course was taken. Format is YYYYT, where YYYY is the year and T is the Term (Terms: 2 = Spring; 3 = Summer; 4 = Fall)

SCHED_NUMB: This is the unique number assigned to each section of a course for a specific period. Used with period it uniquely identifies a course section.

SECT_NUMB: This field identifies a campus defined section number that, in conjunction with Course Abbreviation, Course Number, and Course Suffix, serves to uniquely identify a course offering.

CLASS_STS: This field identifies the current status of an individual's request for a course offering through Regular University or the Extended Education Office.

VALUES:
    0 = Enrolled
    1 = Withdrawn (after drop deadline)
    2 = Dropped (during normal add/drop period)
    3 = Failed Registration Edit

CLASS_STS_DATE: This is the effective date of a change in Class Status.

GRADE: This field identifies an individual's performance in the class.

ENROLLMENT_STS: (At time enrolled in class) This code defines: the current enrollment of a student as related to some prior enrollment, upon which admission will be based. OR, 2) Indicates the admission category for new students.

VALUES:

1 = Continuing Student - An undergraduate or post baccalaureate student who had units enrolled or withdrawn after census at this university or college during the prior term of the regular sessions.

2 = Returning Student - A former undergraduate or post-baccalaureate student returning after an absence of one or more terms of the regular sessions who had no units attempted elsewhere during the absence from this college or university.

3 = Returning Transfer - A former undergraduate or post-baccalaureate student returning after an absence of one or more terms of the regular sessions who had units attempted elsewhere since the previous enrollment.

4 = Transfer - A student new to the regular session of this university or college who had units attempted at any other university or college.

5 = First-Time Student - a First-Time Freshman, or a student classified as postbaccalaureate for the first time, who has earned no college credit after graduation from high school or after graduation from a college or university. Exceptions include:

Students who completed their high school program mid-year, who applied to The California State University for admission to the following fall term, and who enrolled in a California community college in the spring term immediately preceding California State University or College admission.

Students who earned equivalent college credit through the CLEP or AP programs of the College Board.

Students who earned equivalent college credit through military course work only.

Students who earned equivalent college credit through some non-traditional learning experience.

Students who previously earned college credit concurrent with high school enrollment.

STU_LEVEL: This code indicates the current academic level of the student:

Undergraduate Student - A student not holding an acceptable baccalaureate degree. The student will be classified by level on the basis of total units earned, including the reporting campus.

VALUES:

    0 = First Time Freshman - No units earned

    1 = Freshman - 0.1 to 29.9 semester units or 0.1 to 44.9 quarter units.

    2 = Sophomore - 30.0 to 59.9 semester units or 45.0 to 89.9 quarter units

    3 = Junior - 60.0 to 89.9 semester units or 90.0 to 134.9 quarter uni

    4 = Senior - 90.0 or more semester units or 135.0 or more quarter units

    5 = Postbaccalaureate - Holding a baccalaureate or equivalent degree

ADM_ENROLLMENT_STS: Enrollment status at time of admission

ADM_STU_LEVEL: Student level at time of admission

PRI_MAJOR: This is a campus-defined code that indicates the student's primary area of study by school, concentration, and major. Code and literal included in data set.

MINOR: This code identifies a student's minor area of study for the specified degree objective. Code and literal included in data set.

DEG_OBJ: This code shows the degree objective the student is seeking.

VALUES:

    0 = None

    1 = Enrolled in an approved 2-year undergraduate program

    2 = Seeking a Bachelor of Arts Degree (BA)

    3 = Seeking a Bachelor of Science Degree (BS)

    4 = Seeking other bachelor's degree

    5 = Seeking a Master of Arts Degree (MA)

    6 = Seeking a Master of Science Degree (MS)

    7 = Seeking other master's degree

    8 = Seeking a joint doctorate or doctorate

    9 = Other

ACAD_STS: This code indicates whether the student's progress toward a degree objective is satisfactory. Code and literal included in data set.

EOP_CODE: This code identifies a student's status relative to the EOP Program.

VALUES:

    E = Eligible for EOP Program

    G = EOP student during current term, graduated after fall term

    I = Ineligible for EOP Program

    Y = Applied for EOP Program

    S = Bonafide EOP Program

    X = EOP student during current term, withdrew prior to census

CITIZEN_STS: This code identifies whether the student is a citizen of the United States.

VALUES:
   F = Non-U.S. citizen, F visa (student)
   I = Non-U.S. citizen, immigrant (applied for and received Form I-151
      'Green Card').
   J = Non-U.S. citizen, J visa (visitor)
   N = Non-U.S. citizen (undetermined status, or no visa required because not
      entering the US)
   O = Non-U.S. citizen, other visa
   R = Refugee/asylee
   Y = U. S. citizen
   X = Citizenship not determined

SIMS_ETHNICITY: Derived field. Ethnicity as reported to the Chancellors Office. Code and literal included in data set.

SEX: This code identifies the gender of a student.

VALUES:
   M = Male
   F = Female

AGE: Derived field. Age at the beginning of the semester for the period the class was taken.

INSTN_ORIGIN: Derived field. Based on student level at time of admission and Institution of origin:

California High School: first-time freshmen with a California Institution of Origin

Non-Traditional High School: first-time freshmen with a non-traditional institution of origin (GED, Home School, etc.)

Non-California High School: first-time freshmen with an Institution of origin outside California

California Community College: Transfer or returning student with a California Institution of Origin designated as a College

California University: Transfer or returning student with a California Institution of Origin designated as a University

California University, College or School: Transfer or returning student with a California Institution of Origin not designated as a College or University (May include Institutes, vocational schools, etc.)

Non-Traditional University, College or School: Transfer or returning student with a non-traditional institution of origin (Military Credit, etc.)

Non-California University, College or School: Transfer or returning student with an institution of origin outside California

ESL: Derived field: English as a Second Language indicator: Students who took, or were require to take Test of English as a Foreign Language or International English Language Test

VALUES:
    1 = ESL
    0 = Not ESL

FINAN_AID_STS: This code indicates whether a student is receiving financial aid for the term period.

VALUES:
    A = APPLIED
    E = ELIGIBLE FOR AID
    N = NOT RECEIVING AID
    Y = RECEIVING AID
    W = WAIVER

FAMILY_INCOME: Derived: If an individual is classified as a dependent, the annual income of the individual's family is used. If independent, the annual income of the individual is used.

The field may be null if family income was left blank.

VALUES:
    01 = Less than $24,000 per year

    02 = $24,000 to $35,999 per year

    03 = $36,000 to $47,999 per year

    04 = $48,000 to $59,999 per year

    05 = $60,000 to $71,999 per year

06 = $72,000 or more per year

07 = Cannot estimate parents income

08 = No response

CS: Compact for Success

AP: Derived: If a student has AP or IB units accepted > 0 on the Student Exam Credit table or if the student has a Transfer Institution row with acronym = 'ADVPL' and units accepted > 0.

VALUES:
1 = AP credits accepted

0 = No AP credits accepted

DE: Derived: Students who took a Distance Education (DE) or Blended Learning (BL) class during or before taking Psychology 101.

VALUES:
1 = Yes, DE or BL

0 = No DE or BL

TERM_GPA: GPA for units earned for the specified term. Not stored in SIMS. Calculated based on End of Term grade processing and any grade changes processed.

TERM_UE: Units earned for the specified term. Not stored in SIMS. Calculated based on End of Term grade processing and any grade changes processed.

CAMPUS_GPA: GPA for units earned at SDSU. Not from stored data. Calculated based on period class was taken. Includes End of Term and any grade changes processed for the period.

CAMPUS_UE: Units earned at SDSU. Not from stored data. Calculated based on period class was taken. Includes End of Term and any grade changes processed for the period.

TOTAL_GPA: GPA for total units earned. Not from stored data. Calculated based on period class was taken. Includes End of Term and any grade changes processed for the period.

TOTAL_UE: Units earned. Not from stored data. Calculated based on period class was taken. Includes End of Term and any grade changes processed for the period.

APPENDIX I

Psychology 101 Course Registration by Academic Year

Psychology 101 Course Registration by Academic Year

Academic Year		Female	Male	Total (N=18,254)
2006-2007	Fall	794	421	1215
	Spring	810	419	1229
2007-2008	Fall	804	390	1194
	Spring	799	420	1219
2008-2009	Fall	751	463	1214
	Spring	664	406	1070
2009-2010	Fall	906	450	1356
	Spring	589	321	910
2010-2011	Fall	828	390	1218
	Spring	500	340	840
2011-2012	Fall	886	410	1296
	Spring	619	342	961
2012-2013	Fall	975	472	1447
	Spring	549	329	878
2013-2014	Fall	851	503	1354
	Spring	532	321	853
Total		11,857	6397	18,254
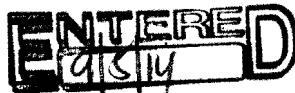
Institutional Review Board
Project Action Summary

Action Date: September 5, 2014   *Note: Approval expires one year after this date.*

Type: __New Full Review ___New Expedited Review ___Continuation Review _X__Exempt Review
          ____Modification

Action: __X_Approved   ___Approved Pending Modification   ___Not Approved

Project Number: 2014-09-002
Researcher(s):   Maureen A. Guarcello Doc SOLES
                  Dr. Lee Hubbard Fac SOLES
Project Title: Blended Learning and Bottlenecks: An Empirical Look at the Importance of Demographic
                  and Performance Analytics

> *Note: We send IRB correspondence regarding student research to the faculty advisor, who bears
> the ultimate responsibility for the conduct of the research. We request that the faculty
> advisor share this correspondence with the student researcher.*

Modifications Required or Reasons for Non-Approval

None

The next deadline for submitting project proposals to the Provost's Office for full review is N/A. You may submit
a project proposal for expedited review at any time.

Dr. Thomas R. Herrinton
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