

Table of Contents

	Page
Abstract.....	iii
Dedication.....	iv
Acknowledgments.....	v
Table of Contents.....	vi
List of Tables.....	x
List of Figures.....	xv
List of Appendices.....	xvi
CHAPTER ONE: INTRODUCTION.....	1
Statement of the Problem.....	1
Research Question.....	3
Aim of the Dissertation in Practice.....	4
Definition of Relevant Terms.....	6
Methodology Overview.....	9
Delimitations, Limitations, and Personal Biases.....	9
Reflections of the Scholar-Practitioner.....	11
Summary.....	12
CHAPTER TWO: LITERATURE REVIEW.....	13
Introduction to the Literature Review.....	13
The Opening.....	15
The Study Topic.....	15

The Context.....	16
The Significance	17
The Problem Statement.....	18
The Organization	19
Conceptual Framework.....	20
Kuh’s Student Success Framework	20
Multiple Measures Placement Rule	22
Co-requisite Support	23
Throughput Optimization.....	24
Review of Research Literature and Methodological Literature.....	25
Multiple Measures for Placement Criteria.....	26
Predictive Validity	28
Co-requisite Support	30
Guided Pathways	33
Disproportionate Impact (DI) on Student Subgroups	36
Throughput student success	38
Review of Methodological Issues.....	40
Quantitative.....	41
Qualitative.....	44
Mixed Methods	49
Synthesis of Research Findings	52
Multiple Measures for Placement	53
Co-requisite Support	55

Guided Pathways	56
Disproportionate Impact (DI) on Student Subgroups	58
Critique of Previous Literature	59
Effects of Eliminating Remedial Courses.....	59
Mixed Results for Default Placement Rule	61
Interpreting Multiple Measures.....	62
Post-AB 705 Implementation	63
Methodology	65
Summary	66
CHAPTER THREE: METHODOLOGY	68
Research Questions and Hypotheses	68
Research Question 1	68
Research Question 2	68
Research Question 3	69
Method	69
Research Design Overview.....	70
Participants.....	71
Data Collection	72
Data Collection Procedures.....	72
Data Collection Tools	72
Data Analysis	75
Ethical Considerations	77
Summary	79

CHAPTER FOUR: RESULTS AND FINDINGS	80
Results	80
Findings.....	96
Discussion.....	105
Summary	107
CHAPTER FIVE: PROPOSED SOLUTION AND IMPLICATIONS	110
Aim Statement	110
Proposed Solutions.....	110
Evidence that Supports the Solution.....	111
Evidence that Challenges the Solution	114
Implementation of the Proposed Solutions	115
Factors and Stakeholders Related to the Implementation of the Solution	117
Timeline for Implementation of the Solution	118
Evaluating the Outcome of Implementing the Solution	119
Implications.....	119
Practical Implications.....	119
Implications for Future Research.....	120
Implications for Leadership Theory and Practice.....	122
Summary of the Dissertation in Practice	124
References.....	129
Appendices.....	158

List of Tables

	Page
Table 1. Throughput Success Rates of Mathematics Students in STEM Pathway.....	81
Table 2. Throughput Success Rates of Mathematics Students in Non-STEM Pathway.....	81
Table 3. Throughput Success Rates of Mathematics Students in STEM pathway by term	82
Table 4. Throughput Success Rates of Mathematics Students in non-STEM pathway by term.....	83
Table 5. Two Proportions z-Test for the Difference between Observed and Predicted success rates for the Placement Level 1 (Direct) in STEM pathway.....	85
Table 6. Two Proportions z-Test for the Difference between Observed and Predicted success rates for the Placement Level 2 (Coreq) in STEM pathway.....	85
Table 7. Two Proportions z-Test for the Difference between Observed and Predicted success rates for the Placement Level 3 (Pretransfer) in STEM pathway	85
Table 8. Two Proportions z-Test for the Difference between Observed and Predicted success rates for the Placement Level 1 (Direct) in Non-STEM pathway	86
Table 9. Two Proportions z-Test for the Difference between Observed and Predicted success rates for the Placement Level 2 (Coreq) in Non-STEM pathway	86

Table 10. Two Proportions z-Test for the Difference between Observed and Predicted success rates for the Placement Level 3 (Pretransfer) in Non-STEM pathway	86
Table 11. Kruskal-Wallis Rank Sum Test for Throughput Grades by Placement Level	87
Table 12. Pairwise Comparisons for the Mean Ranks of Throughput Grades by Levels of Placement	87
Table 13. Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level for Fall 2019.....	87
Table 14. Pairwise Comparisons for the Mean Ranks of Throughput Grades for Fall 2019	88
Table 15. Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level for Spring 2020	88
Table 16. Pairwise Comparisons for the Mean Ranks of Throughput Grades for Spring 2020.....	88
Table 17. Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level Filtered by Age: 25 years and below	89
Table 18. Pairwise Comparisons for the Mean Ranks of Throughput Grades by Levels of Placement Filtered by Age: 25 years and below	89
Table 19. Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level	

Filtered by Gender: Female	89
Table 20. Pairwise Comparisons for the Mean Ranks of Throughput Grades by Levels of Placement	
Filtered by Gender: Female	90
Table 21. Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level	
Filtered by Ethnicity: Hispanic/Latino.....	90
Table 22. Pairwise Comparisons for the Mean Ranks of Throughput Grades by Levels of Placement	
Filtered by Ethnicity: Hispanic/Latino.....	90
Table 23. Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level	
Filtered by DSPS Status: Yes	91
Table 24. Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level	
Filtered by EOPS Status: Yes	91
Table 25. Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level	
Filtered by CalWORKs Status: Yes.....	91
Table 26. Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level	
Filtered by Pathway: Non-STEM	92

Table 27. Pairwise Comparisons for the Mean Ranks of Throughput Grades by Levels of Placement	
Filtered by Pathway: Non-STEM	92
Table 28. Frequency Table for Nominal and Ordinal Variables based on throughput success rate	
Filtered by Successfully Completed Category	93
Table 29. Two Proportions z-Test for the Difference in Successful Completion between F19 and S20	
Disaggregated by Age: 25 Years and Below	94
Table 30. Two Proportions z-Test for the Difference in Successful Completion between F19 and S20	
Disaggregated by Gender: Female	94
Table 31. Two Proportions z-Test for the Difference in Successful Completion between F19 and S20	
Disaggregated by Ethnicity: Hispanic/Latino	94
Table 32. Two Proportions z-Test for the Difference in Successful Completion between F19 and S20	
Disaggregated by DSPS: Yes	94
Table 33. Two Proportions z-Test for the Difference in Successful Completion between F19 and S20	
Disaggregated by EOPS: Yes	95
Table 34. Two Proportions z-Test for the Difference in Successful Completion between F19 and S20	

Disaggregated by CalWORKs: Yes.....95

Table 35. Two Proportions z-Test for the Difference in Successful Completion
between F19 and S20

Disaggregated by Pathway: Non-STEM.....95

List of Figures

	Page
Figure 1. Kuh's 'What Matters to Student Success' Schematic.....	21
Figure 2. Throughput Success Rates for STEM Pathway.....	84
Figure 3. Throughput Success Rates for non-STEM Pathway	84

List of Appendices

	Page
Appendix A. Revised Placement Criteria at participating college for Statistics Pathway.....	158
Appendix B. Revised Placement Criteria at participating college for STEM Pathway.....	159
Appendix C. Recommended AB 705 Placement Criteria for Statistics/ Liberal Arts Mathematics	160
Appendix D. Recommended AB 705 Placement Criteria for BSTEM Mathematics	161
Appendix E. MMAP Decision Tree Nodes by Transfer-Level Subject	162
Appendix F. Placement in STEM pathway: By Demographics for Fall 2019 and Spring 2020.....	163
Appendix G. Placement in Non-STEM pathway: By Demographics for Fall 2019 and Spring 2020	164
Appendix H. Placement in STEM pathway: By Status for Fall 2019 and Spring 2020.....	165
Appendix I. Placement in Non-STEM pathway: By Status for Fall 2019 and Spring 2020.....	166
Appendix J. IRB Approval from Creighton University.....	167

CHAPTER ONE: INTRODUCTION

Community colleges are positioned to serve the needs of the community by offering programs that have an immediate impact in the local community as well as in refining the lives of the students (CCRC, 1998). The focus of community colleges is to provide access to success for all students (CCCCO Key Facts, 2019). Student access and student success have become the focal point in the decision, delivery, and implementation of curricular and college policies.

Statement of the Problem

Low success rates have been a long-standing problem among transfer-level students in California community colleges. In central California, particularly, the low throughput success rates have been attributed to the improper student placement that used a standardized placement score at the time of admission to the college. Most students, particularly those of color, have been under placed in remedial courses with long sequences before they can complete the transfer-level course to transfer out to four-year universities (PPIC Higher Education Center, 2016). Currently, the throughput success rates of California community college mathematics students (statewide) who completed their transfer-level courses in the first year of college for 2017-18 is 14% (CCCCO Scorecard, 2018), while the central California community colleges showed 10% throughput success rate for transfer-level math students for 2017-18 (Central Valley Higher Education Consortium, 2018). The dismally low success rates are a major concern for both students and institutions alike.

Based on student performance on standardized placement tests such as ACCUPLACER and COMPASS, more than 75% of incoming students at community

colleges in the state of California have been required to take remedial classes, particularly for math and English courses (Rodriguez & Mejia, 2016). Originally, the remedial classes were intended to assist underprepared students in refreshing and mastering necessary skills in English and Mathematics, which may take up to two years to complete due to the scaffolded sequence of prerequisite courses. Research from the last decade has shown that, despite the original intent, the remedial courses were the biggest barrier for student success (Hern & Snell, 2014).

In order to address the long-standing problem of low success rates among students under-placed in remedial courses, the California lawmakers passed a legislature, Assembly Bill AB 705, which requires community college districts to “maximize the probability that a student will enter and complete transfer-level coursework in Math and English within a one-year timeframe by utilizing assessment measures that include high school performance to achieve this goal” (AB705, 2017, para 1). The law was implemented across all 115 California community colleges in Fall 2019.

AB 705 requires colleges to stop using a single metric of placement (i.e., the standardized tests) and instead use students’ high school grades and past achievement (collectively known as the multiple measures of assessment) as the primary means of student placement in English and Mathematics. Alternative metrics of placement such as high school grades, GPA, and prior completion of prerequisite courses in high school, have been shown to be far more reliable indicators of student performance in college (Bahr, 2010; Belfield & Crosta, 2012; Hern & Brezina, 2016). College students who took Mathematics and English courses were able to get through transfer-level courses unfettered when they are not placed in a single pre-transfer-level course, provided they

took courses that were redesigned with high support system in place (Barnett, et al., 2018; Belfield & Crosta, 2012; Cullinan, et al., 2018; Scott-Clayton, et al., 2012). Results from retrospective analysis projected that a majority of these Mathematics and English students fared better across all student populations from all levels of high school performance (Hayward, 2017; Hayward & Willett, 2014).

Research Question

The study pertains to Mathematics students who completed their transfer-level course in central California community colleges in the academic year 2019-2020. When students enter the college, if they desire to transfer out to four-year university, they will be asked to select their pathway choice as either STEM or non-STEM. Then, they will be assigned to one of the three placement levels based on the multiple measures of placement assessment. Placement Level 1 allows students to start directly at a transfer-level course with no required support. These students showed high HSGPA scores and passed the prerequisite courses. Placement Level 2 allows students to start directly at a transfer-level course but with a mandatory corequisite support course. These students have intermediate HSGPA scores and have not completed the prerequisite courses. Placement Level 3 allows students to start at a pre-transfer-level course which is one level below transfer-level and then complete the transfer-level course in the next semester or within a one-year timeframe. These students have low HSGPA and have not taken any past math courses (or had taken too long ago). The overarching question in this study is to see to what extent the placement levels have an effect on the throughput success rates of mathematics students who successfully completed their transfer-level course within a one-year timeframe (known as throughput).

Research Question 1

How does the throughput success rate in STEM and non-STEM pathways compare with those of the predicted baseline metrics set by the California Community Colleges Chancellor's Office (CCCCO)?

Research Question 2

To what extent, if any, does a significant difference exist in the throughput grades among those who started at one of the three placement levels?

Research Question 3

To what extent, if any, does a significant difference exist in the proportions of throughput success rates for Fall 2019 and Spring 2020 among student categories disaggregated by age, gender, ethnicity, DSPS, status, EOPS status, CalWorks status, and pathway choice?

Aim of the Dissertation in Practice

The AB 705 California law has mandated placement reforms that colleges must no longer use the placement tests but instead incorporate multiple measures of assessment policy for student placement that uses high school achievement data, including the HSGPA (Belfield & Crosta, 2012). This change is expected to place most students directly in transfer-level courses, thus eliminating the traditional, remedial sequence of courses. Also, students will get to choose their desired pathways, such as STEM or non-STEM, at the time of enrollment so that the guided pathways will help them complete their sequence of required courses for transfer in a timely manner. The purpose of the study is to validate the effectiveness of the placement reforms in central California community colleges to determine if the changes truly maximized the throughput success

rates (AB705 Student Success Act, 2017). The purpose of the study aligns closely with Kuh's framework for student success wherein the institutional reforms as well as the student services and support are designed to enhance student learning and student success.

Rationale

While the AB 705 law prohibits colleges from placing students in remedial courses, many institutions have raised concern that not all their students are prepared for the transfer-level course or that their students are more interested in an Associate's degree or diplomas rather than transferring to a university. The Chancellor's Office, understanding the complexity of the placement process, has allowed colleges to innovate their local placement criteria based on their local student needs (such as a pre-transfer-level course or mandatory support courses). However, colleges have until Fall 2021 to validate their changes and show that their innovation *maximized* throughput student success by meeting or exceeding the state's project success rates for each placement level (Hope & Stankas, 2018).

Relevance

The mathematics department in the participating college in this study, like many other central California community colleges, has revised their placement criteria to allow underprepared students (determined based on low HSGPA and incomplete prerequisites) to be placed in the pre-transfer-level course. It is an innovation that is being tested which deviates from the state's default guideline that requires all students to be placed directly in transfer-level courses. Therefore, it is relevant to study if the placement criteria (starting course) has an effect on throughput student success by comparing the success

rates of students who started at different placement levels and then completed the transfer-level course, all in a one-year timeframe. It is germane to learn if the elimination of remedial courses truly eliminates the barrier for college success. A non-significant difference result could mean that placement is not the primary reason for student success and that other factors influence student success even if they start at the pretransfer-level.

Significance

The significance of this study lies in its relevance to the urgent reforms undertaken to uphold the mission of California community colleges, which is to provide all students unfettered access and success in their learning and completion. The study is not only relevant but significant because of the urgency with which early evidence is sought by the state to validate the effectiveness of the reforms. The findings from the study will help strengthen and refine the implementation process as well as the criteria for student placement. The study will benefit key stakeholders, namely, the college leadership, the mathematics department, the curriculum committee, the Office of Institutional Effectiveness, the Admissions department, the counselors, the faculty, the students, and the community at large.

Definition of Relevant Terms

The following terms were used operationally within this study.

Placement criteria refer to the process involved in determining the starting course level (initial course level) of a student enrolled in the community college for the first time.

Placement level refers to one of the three placement levels in which a student may be placed when entering college for the first time based on their multiple measures of

assessment. The three levels are Placement Level 1 (direct placement in transfer-level), Placement Level 2 (transfer-level plus mandatory support course), and Placement Level 3 (pretransfer-level followed by transfer-level in the subsequent term).

Multiple measures of assessment refer to incorporating two more criteria for assessment and placement (California Community College Assessment Association, 2001). Under a multiple measures approach, standardized placement testing is no longer the primary means of assessing if a student is prepared for college-level coursework and is prohibited by California law (AB705 Student Success Act, 2017). This term is sometimes used interchangeably with the following terms: *multiple measures*, *multiple measures for placement*, *multiple measures placement policy*, and *multiple measures of assessment policy for placement*.

Guided pathways refer to a highly structured approach to student success that provides all students with a set of clear course-taking patterns that promotes better enrollment decisions and prepares students for future success (California Community Colleges Chancellor's Office, 2018). At the time of enrollment, the students typically choose one of two pathways, either STEM or non-STEM pathways.

HSGPA stands for High School Grade Point Average.

STEM Pathway prepares students for transfer degrees and careers in science, technology (computer science), engineering, and mathematics.

Non-STEM Pathway prepares students for transfer degrees and careers in liberal studies, arts, language arts, humanities, and social sciences.

Co-requisite support refers to the mandatory support class that students are enrolled concurrently with the transfer-level course for just-in-time remediation of pre-requisite content.

Transfer-level refers to the last course in the sequence that a student must complete in order to transfer to a four-year university.

Pre-transfer level refers to a math course that is one course level below the transfer-level course.

Throughput success refers to a student's successful completion of the math course sequence culminating in the transfer-level course within a one-year timeframe (two semesters or three quarters) (MMAP Team, 2018).

Throughput student success rate refers to the number of students who successfully complete the transfer-level course at the end of a course sequence divided by the number of students in the initial cohort with a grade of 70% (C) or higher in their first attempt, expressed as a percentage. For the students whose starting course (first attempt) was pre-transfer level, the throughput rate is defined as the percentage of these students who successfully completed the transfer-level course in the sequence within one year of the starting course (MMAP Team, 2018).

DSPS refers to the Disabled Students Programs and Services (DSPS) program. Eligible students who participate in this program have DSPS status.

EOPS refers to the Extended Opportunities Programs and Services (EOPS) program. Eligible students who participate in this program have EOPS status.

CalWORKs refers to the California Work Opportunity and Responsibility to Kids (CalWORKs) program. Eligible students who participate in this program have CalWORKs status.

Disproportionate impact refers to the condition where some students' access to college-level coursework is hampered by inequitable practices, policies, and approaches to student placement (Hayward, 2017).

Methodology Overview

Using retrospective data as the initial baseline, the study results can reveal if there was an improvement in the throughput success rates or not. Additionally, given the AB 705 mandate, the state's estimated success rates must be met or exceeded to determine if the reforms and any innovations (that deviate from the prescribed guidelines) were valid or not. That is, all subsequent changes to placement, curriculum, and pathways should result in maximizing the throughput rates (Hayward, 2017).

Delimitations, Limitations, and Personal Biases

Delimitations

In relation to data collection, the study information was obtained from Fall 2018 to Spring 2020 sections through secondary data, upon approval from IRB. The student-identifying information in the data was removed to keep the data anonymous. The data on demographics, course enrollment details, grades, credits, and completion, special status such as DSPS, EOPS, and CalWORKs, placement information, and guided pathways were obtained and analyzed from the participating subjects, retrospectively. No personal details have been stored and thus cannot be traced back to the individuals.

Limitations

The first limitation in obtaining secondary archival data indicates that the independent variable could not be manipulated. The effects have already occurred, and it cannot be guaranteed that the independent variables caused a change in the dependent variable. The second limitation is the inability to construct random samples as there is no opportunity to randomly choose participants for experimental and control groups (as one would in an experimental design) since the effects have already occurred. The third limitation is that the study is testing the effectiveness of the revised placement policies that were put in place in Fall 2019. The newness and recency of the implementation do not allow for comparison across multiple years, as this is the beginning year post-AB-705 implementation. The results from this study will be used as early evidence of the policy implementation results. In addition, in the middle of the study, the world experienced the COVID-19 pandemic which caused severe disruption to daily functioning and management of life, family, and work for months on lockdown. The data for Spring 2020, therefore, has been impacted both directly and indirectly due to the unforeseen and upended health crisis.

Assumptions

The literature review revealed that the estimated success rates and predictive validity results were based on then-current practices which included the use of placement tests as the primary means of student placement. The study data was obtained from the participating institution which applied multiple measures placement policy based on high school performance including HSGPA and prior course completion of the pre-requisites.

It was understood and assumed that the current placement criteria are implemented truthfully and in compliance with the California law.

Reflections of the Scholar-Practitioner

As a new researcher, the reflective practices of the Ignatian tradition has brought forth a shift in my worldview and in the way I approach interdisciplinary enterprises such as education and administration. It helped me seize on the leadership opportunity to trailblaze the post-AB705 world with my early evidence on the effectiveness of educational reforms, amid the COVID-19 pandemic. The impact of COVID-19 on Spring 2020 data has been an interesting statistical challenge. My approach of salvaging the data by dissecting the research question into different comparisons by term, pathways, and demographics will hopefully lead the way for others to follow. Sharing findings with the key stakeholders in the participating college, in particular the mathematics department, the Office of Institutional Effectiveness, and the AB705 task force will help refine and strengthen the local placement criteria. Moreover, disseminating the findings in conferences and consortiums such as Central Valley math consortium, CAP, CCCCCO and MMAP may lead to statewide conversation. Results may establish a new trend or approach towards response and mitigation efforts in times of emergency (epidemic, wildfires, and poor air quality). Being early evidence study, the future follow-up research can be expanded to compare differences in throughput based on distance education (virtual, hybrid, correspondence, fully online) with those of traditional in-person courses to validate the effectiveness of online courses.

Summary

The educational reforms and recommendations from the last decade have been influential in passing the Student Success Act, AB 705. The law was implemented in Fall 2019 and all California community colleges are required to implement the multiple measures of assessment which uses high school data for placement instead of a single placement test to determine student placement when entering college for the first time.

In this study, I wanted to determine if there is a significant difference in the throughput success rates of mathematics students based on their placement level. The data was disaggregated by students' demographics and special services. The study findings helped ascertain if placement had a significant influence on the throughput success rates based on the guided pathway choice as well as the semester enrolled.

This study is a direct response to the call from the California Chancellor's Office asking colleges to conduct their own analysis to ensure that the local data aligns with the statewide findings. More importantly, the findings will help improve the accuracy of decisions related to the placement processes, concurrent support, and guided pathways at the institutional level.

CHAPTER TWO: LITERATURE REVIEW

This chapter contains a detailed review of literature related to California community colleges, mathematics courses in community college, community college student population, redesigned curriculum, guided pathways, placement policy, measures, criteria for transfer-level mathematics courses, and throughput student success. The introduction of the literature review is segmented into six subsections, namely, “(1) the opening, (2) the study topic, (3) the context, (4) the significance, (5) the problem statement, and (6) the organization” based on recommendations from Machi and McEvoy (2016, p. 141). The introduction is followed by the conceptual framework upon which the study is built. A detailed review of research and methodological literature was provided, with a special section dedicated to issues in methodology. A synthesis of research findings was presented, followed by a critique of previous research. The chapter ends with a summary.

Introduction to the Literature Review

Community colleges become the first point of entry for higher education in the United States for a majority of adult students comprised of minority, low-income, first-generation learners, and students of color (CCRC, 1998). Community colleges serve the most substantial proportion of the student population in higher education across the United States (CCRC, 2019). There are 115 community colleges across California. Success in mathematics courses is essential to college completion and career preparation (CCCCO, 2019). However, past data from California community colleges (the 2010-2011 cohort tracked through 2015-2016) showed that students who enrolled in remedial mathematics courses 2 to 4 levels below the transfer-level had a completion rate of 34%

at the level of intermediate algebra (pre-transfer-level) within six years at the college (CCCCO Scorecard, 2018; Central Valley Math Pathways Task Force (CVMPTF), 2018).

A common conclusion from many studies (Bahr, 2010; Chen, 2013; Hayward & Willett, 2014; Rodriguez et al., 2017) point to remedial, developmental courses, particularly in mathematics, as being the biggest impediment to student success. The researchers also indicated that misalignment of pathways and placement of students into the remedial sequence were major reasons that an overwhelming majority of students, particularly those of color, were unable to complete their transfer-level courses (Fitzpatrick & Sovde, 2019; Jones, 2014; Leahy & Marshall, 2019).

To address the issue of low student success, California lawmakers passed the Student Success Act, Assembly Bill AB 705, which was signed into law on October 13, 2017, and took effect on January 1, 2018. The bill requires community college districts to “maximize the probability that a student will enter and complete transfer-level coursework in Math and English within a one-year timeframe by utilizing assessment measures that include high school performance to achieve this goal” (AB705 Student Success Act, 2017, para 1). The assessment measures include using one or more measures of students’ prior performance, such as high school coursework, high school grades, and high school grade point average (known as multiple measures of assessment for placement), to determine course placement when entering college. The bill prohibits the use of a single measure of placement, such as ACCUPLACER or Compass placement test scores. AB 705 mandates all California community colleges to follow the multiple measures of assessment policy when placing students using the placement rule criteria.

The Opening

Before the law, California community colleges typically used the placement test score as the sole deciding factor to place the majority of the students into the remedial sequence, no matter their high school math achievement. With the implementation of multiple measures, California colleges have revised their placement rule to consider a combination of scores, namely, HSGPA scores, high school coursework completion that serves as the pre-requisite, and prior math course completion to determine the starting course level (AB705 Student Success Act, 2017). The multiple measures of assessment policy implemented into the placement rule criteria assure that almost all students will be placed directly in a transfer-level course. The use of multiple measures is expected to improve the throughput success rates dramatically as an overwhelming majority of students will be placed into transfer-level courses, thus bypassing the impediment caused by the remedial courses. The throughput success refers to the successful completion of the transfer-level course within a one-year timeframe, from the time of entry.

The Study Topic

It has been documented that mathematics is a barrier to student success in college education (Bahr, 2010; CCRC, 2014; Central Valley Math Pathways Task Force (CVMPTF), 2018; Rodriguez et al., 2017). The community colleges in the central valley region of California are more disadvantaged because of the location as educational advancements, technology, infrastructure, or sophistication take longer to arrive (Central Valley Math Pathways Task Force (CVMPTF), 2018; Rodriguez et al., 2018). The throughput success rates of transfer-level students in California community colleges are quite low, particularly in mathematics (Bailey et al., 2010; CCRC, 1998). The focus of

the study topic will be the impact of AB705 Bill in California community colleges in the following areas: placement criteria, curricular redesign, guided pathways, co-requisite support, and disproportionate impact on student groups. The study topics are related to throughput student success rates in mathematics transfer-level courses in central California community colleges.

The Context

In July 2018, the California Community Colleges Chancellor's Office (CCCCO) released a memorandum recommending 'default' placement rules as a minimum threshold of compliance for colleges to adopt (Hope & Stankas, 2018). Appendices C and D provide the state recommended placement rules for Statistics/Liberal Arts pathway and Business STEM pathway. According to the default placement rule, mathematics students will be able to directly start at the transfer-level course instead of starting at a long sequence of traditional remedial courses. Most importantly, the default placement rule will place all students directly into transfer-level courses (with or without recommended support), as appropriate for their chosen pathways. Typically, the STEM pathway students (heading for math-intensive majors) will be placed in the transfer-level Precalculus course and the non-STEM pathway students (heading for non-math-intensive majors) will be placed in a transfer-level Statistics course. Their starting course could be a transfer-level course with no recommended co-requisite support or transfer-level course with recommended co-requisite support.

For colleges that did not want to use the statewide default placement rules, they must examine their local needs and data to develop their own placement rules (Hern, 2019). The Chancellor's Office allows colleges to diverge from the state's default

placement rule, such as, including a pre-transfer-level (remedial) course into their placement rule or making the co-requisite support mandatory, provided they validate their changes to ensure that the “throughput of those students is at least as high as direct placement would have been” (Hope & Stankas, 2018, p. 9).

The Significance

The Chancellor’s Office (CCCCO) commissioned researchers from the Multiple Measures Assessment Project (MMAAP) to analyze statewide data from 2007 to 2014 using high school grades. According to their findings, students with low GPAs who were placed directly in transfer-level statistics courses were three times more likely to complete than their peers who were placed in a pre-transfer level course (29% Vs. 8%) (Hayward & Willett, 2014; Hern, 2019; RP Group, 2014). Those who received co-requisite support in their transfer-level course were five times more likely to complete than their pre-transfer level peers (45% Vs. 8%) (Hayward & Willett, 2014; Hern, 2019; RP Group, 2014). The MMAAP data and other most recent literature (Hern, 2019; MMAAP Team, 2019; RP Group, 2018; Rodriguez et al., 2018) quote the data and results based on studies conducted before AB 705 was fully implemented in Fall 2019. That is, the students’ data were collected before the placement tests were fully removed and before the students were taught under the redesigned curriculum, embedded support, and revised placement measures throughout California colleges.

Given the recency of AB 705 implementation across all California community colleges, it is of utmost importance to measure the effectiveness of the curricular reforms, particularly the placement system. The Chancellor’s Office (CCCCO), as well as most recent research studies related to throughput rates, exhort colleges to conduct local

research and report their findings by Fall 2021 to validate the effects of multiple measures of assessment in placement decisions (Hayward, 2017; Hope & Stanskas, 2018; MMAP Research Team, 2018). The issue of low throughput student success in transfer-level mathematics courses is pressing and maximizing the success rate has become a serious concern in California community colleges. Therefore, the study that I am undertaking is quite significant and timely in determining the effects of student placement in maximizing throughput success.

The Problem Statement

The National Center for Education Statistics reported a nationwide downward trend of performance in mathematics and low graduation rates in postsecondary institutions. The graduation rates within 150% of normal time for degree completion of first-time, full-time undergraduates was 31.6% for the year 2016-17 (National Center for Education Statistics, 2019). The existing literature on success rates of transfer-level mathematics students in California community colleges demonstrated that the throughput rates were unacceptably low, as documented in the Student Success Scorecard by California Community College Chancellor's Office (CCCCO). Most recent data from the community colleges in central California showed that among 23,854 students seeking a degree or transfer, who were enrolled for the first time at a community college in the central valley region in 2017-18, only 10% completed a transfer-level Math course within the first year. In comparison, the statewide outcome showed only 14% throughput success rate (Central Valley Higher Education Consortium, 2018).

Among the many factors attributed to the very low success rate, the primary reason was ascribed to the inaccurate and disproportionate placement of students into

remedial courses. Most students, particularly those of color and other disadvantaged backgrounds, tend to get referred to remediation based on a standardized placement test score taken at the time of entering college (Bahr, 2010; Bailey et al., 2010; Bettinger & Long, 2009). These students get entangled in the web of the developmental course sequence, thus preventing them from completing college in a timely manner (Boatman, 2012; Calcagno & Long, 2008; Gibbons et al., 2019).

In the post-AB705 world, the effectiveness of the reforms such as changing the placement criteria, eliminating the remedial sequence, designing concurrent support, and directly placing all students into transfer-level math courses needs to be validated. The past studies, conducted before AB 705 implementation, projected high success rates and increased likelihood of success, even for low performing students (Barnett, et al., 2018; Belfield & Crosta, 2012; Harper et al., 2009; Hayward & Willett, 2014; Jaggars et al., 2015). However, it remains to be seen whether the changes, in reality, post-AB 705 implementation, can dramatically improve the low throughput success rates without adversely impacting any student subgroups (Hern, 2019; MMAP Research Team, 2018; Martorell & McFarlin, 2011; Melguizo et al., 2011).

The Organization

The literature review chapter is organized in a distant-to-close approach. The review is mainly synthesized around the topic of maximizing student success using Kuh et al.'s (2006) student success and student engagement framework as the conceptual framework. With the theoretical underpinnings of Kuh's framework, I was able to make connections in the literature review on the recent educational reforms in California

related to multiple measures of assessment, placement criteria, and throughput student success.

Conceptual Framework

The conceptual framework is based on Kuh's framework on student success and student engagement that was developed based on relevant literature, emerging findings, and informed perspective on policies, programs, and practices related to student performance and student success in postsecondary education (Kuh et al., 2006). Kuh's student success and student engagement agenda are heavily influenced by the works of Astin, Pascarella, Terenzini, Tinto, Perna, and Thomas (Astin 1977, 1984, 1985, 1993; Pascarella & Terenzini, 1991, 2005; Perna & Thomas, 2006; Tinto, 1995).

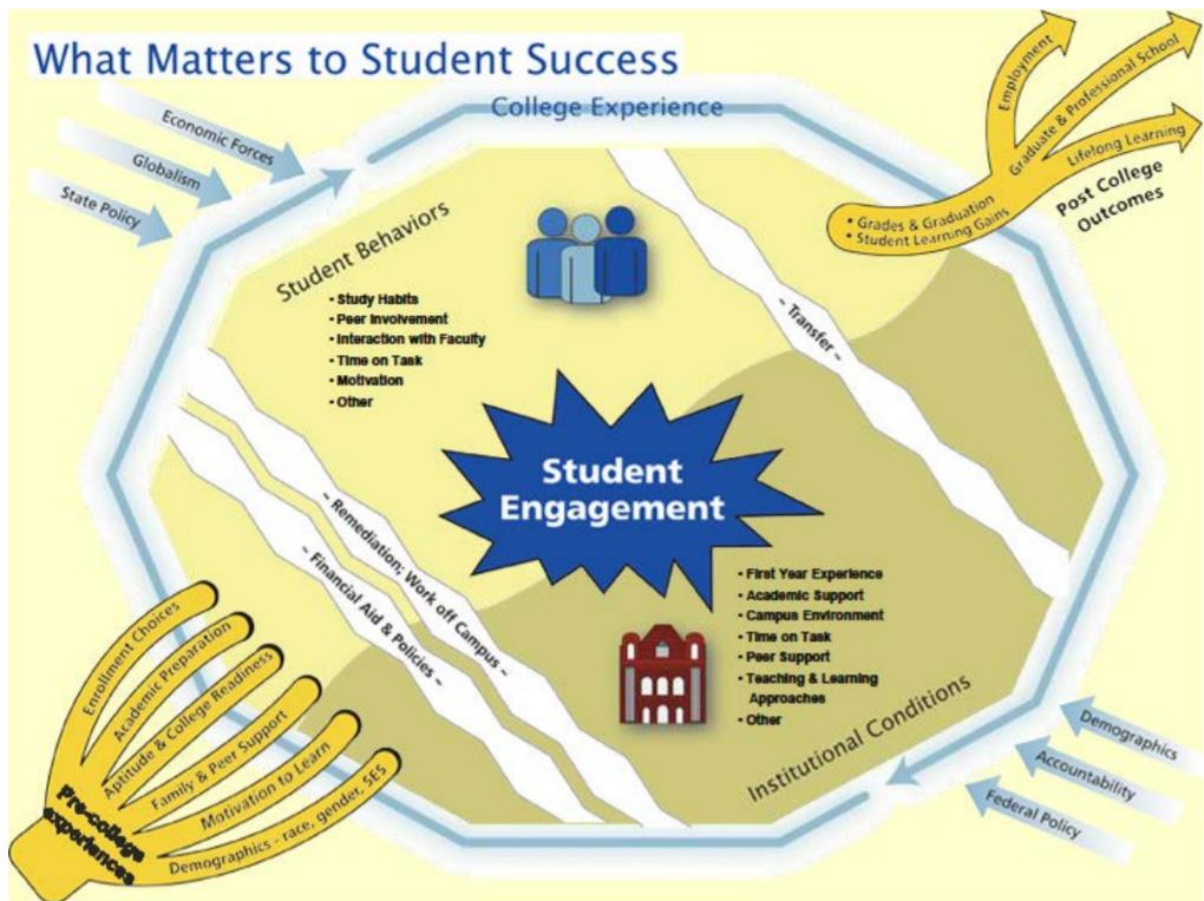
Kuh's Student Success Framework

Kuh's framework of student success and student engagement outlined the connections between student efforts, student engagement, and student outcomes affected by the college environment, experience, and educational process, which in turn determines student success collectively. Kuh's framework schematic (see Figure 1 below) first appeared in the National Postsecondary Educational Cooperative (NPEC) that was commissioned in 2006 to review, synthesize, and theorize student success perspectives based on extant literature and to identify, correlate, and incorporate new models and recommendations to promote student success. The schematic further brings together multiple student success frameworks in existing literature such as utilizing organizational development theory in pursuit of "inclusive excellence" as promulgated by Williams et al. (2005), fostering "equity-mindedness" through educational reforms as proposed by Bensimon (2007), guiding campus actions to foster student persistence by

Tinto and Pusser (2006), and overcoming equity gap across race-ethnicity, socio-economic class, and income as outlined by Perna and Thomas (2006). Reports from other initiatives such as Lumina Foundation and Achieve the Dream (ATD) were also influential in Kuh et al. (2006)'s design of the framework schema wherein enacting policies, tracking with data, engaging faculty, staff, and students, assessing strategies based on evaluation results, and establishing infrastructure for continuous improvement and accountability are integrated for holistic support as in Figure 1.

Figure 1

Kuh's 'What Matters to Student Success' Schematic



Note: Adapted from Kuh et al., (2006, p. 8)

The student success framework schema developed by Kuh et al. (2006) is particularly relevant to the problem of low throughput success rates as present in community colleges. The schema depicts pre-college experiences as well as college experiences represented by students' behaviors and institutional conditions, followed by post-college outcomes (Kinzie & Kuh, 2016, p. 6). The wholesome approach of considering multiple perspectives and aspects that affect a student individually, instructionally, and institutionally as well as accountability in policy reforms and practices makes the framework directly applicable to the given problem faced by community colleges to dramatically improve the throughput success rate for all its students.

Multiple Measures Placement Rule

The Multiple Measures Assessment Project (MMAP) team has been on a mission to identify, analyze, and validate multiple measures of assessment data (including High School transcript data, noncognitive variable data, & self-report High School transcript data) to predict student success in transferable college-level courses. The team conducted their research on statewide data obtained from 2007 to 2014 to find if a correlation existed between placement and student success. Their projected findings indicated that there were no identifiable groups who completed a transfer-level course at a higher rate when placed into developmental education than if placed directly into transfer-level (Hayward & Willett, 2014; RP Group, 2014). More specifically, the MMAP findings could not find any student subgroups based on ethnicity, gender, EOPS, and DSPS status, ELL status in high school, and Pell-eligible students to be negatively impacted in their

throughput success when placed directly in transfer-level courses (MMAP Research Team, 2018).

When legislating AB 705 based on early evidence, the proposed ability to make a significant impact on student success became the critical proponent in the Chancellor's Vision for Success. The Chancellor's Office of California Community Colleges (CCCCO) has since adopted MMAP findings (AB705 Student Success Act, 2017; CCC Student Success Task Force, 2011; Hayward & Willett, 2014; CAP Central, 2018) to place students into courses that give them the best chance of completing a transfer-level course within a year. The AB 705 law was implemented in Fall 2019 across all California community colleges requiring colleges to use multiple measures of assessment for student placement decisions.

The default placement rules developed by the Chancellor's Office recommended colleges to place students directly in transfer-level courses unless there was clear evidence that students are less likely to succeed (Hope & Stankas, 2018). The default rule has three placement levels that indicated the starting course for the entering student. These levels placed students into transfer-level courses. The levels were distinguished based on a cutoff criterion (e.g. students with HSGPA ≥ 3.0 were not recommended support for transfer-level Statistics course) to determine whether co-requisite support should be recommended or not, thereby eliminating any placement into the remedial sequence.

Co-requisite Support

The pioneers of the California Acceleration Project (CAP) were instrumental in advocating accelerated, redesigned curriculum with shorter pathways that placed students

directly at the transfer-level courses. Under-prepared students who would then skip remedial sequence and enroll directly in transfer-level courses must be offered personalized co-requisite support involving just-in-time remediation (Hern & Snell, 2014; Hern & Snell, 2013; Huntsman et al., 2016). According to the state's guidelines and their recommended default placement rule, mathematics students with low high school achievement (HSGPA < 2.3 with no prior math coursework for non-STEM pathway and HSGPA \leq 2.6 with prior Algebra coursework for STEM pathway) should still be placed directly in transfer-level courses with additional academic and concurrent support recommended for those students (Hope & Stankas, 2018). The co-requisite approach is found to be beneficial to students who may need the assistance in basic skills that they have not mastered by providing just-in-time remediation, without having to front-load the content before taking transfer-level course (Bettinger & Long, 2009; Calcagno & Long, 2008; Logue et al., 2018). One of the main benefits of co-requisite support is that it helps eliminate the need for a remedial sequence of courses and backs up accelerated, redesigned curriculum (Edgecombe N., 2011; Hanover Research Council, 2015). Also, many studies have shown little indication that remedial sequence of courses improved academic outcomes (Cullinan, et al., 2018; Hern & Snell, 2013; Rodriguez et al., 2018).

Throughput Optimization

Throughput is described as the total number of students who successfully complete the transfer-level courses within a one-year timeframe or lesser (Hayward, 2017). Throughput success rates refer to the percentage of students who successfully complete transfer-level Math courses with a grade of C or better within the primary semesters of their first attempt in a one-year timeframe (MMA Research Team, 2018).

Mathematically, it is the number of students who successfully complete the transfer-level gateway at the end of a course sequence divided by the number of students in the initial cohort (Hayward, 2017). The concept of throughput relates directly to maximizing student success. One of the ways of optimizing throughput is to reform placement decision rules used by colleges. Based on the predictive validity measures projected by statewide findings (CCCO, 2019; Hope & Stankas, 2018), studies conducted by other research groups (Barnett et al., 2018; Cullinan et al., 2018; Hayward, 2017; Hayward & Willett, 2014; MMAP Research Team, 2018; Rodriguez et al., 2018), as well as studies conducted by the local research teams (Bakersfield College, 2013; Belfield & Crosta, 2012; Cuyamaca College, 2019; Henson et al., 2017; Jenkins & Cho, 2012; Regional Education Laboratory (REL), 2011), it has become evident that among other curricular changes, the most effective reforms must happen in the placement system. By switching to multiple measures of assessment for placement using High school GPA, past math courses completed, and other coursework instead of a single placement score, it is expected that more students are likely to be placed in their correct starting course level without having to be placed in remediation.

Review of Research Literature and Methodological Literature

The review of research literature is carried out to examine the social and historical construction of policies, practices, and theory verification in order to orient changes for real-world applications in higher education. The following pages explore the qualitative and quantitative studies of placement research and student success, particularly in mathematics and sciences. The aim is to provide a systematic review that explains how particular interventions or innovations affect specific outcomes such as student success,

academic achievement, and transfer rates. The scope of the literature review is focused on student success in mathematics courses concerning placement criteria to maximize throughput rates. The focus includes literature related to AB705 on California colleges in terms of throughput student success as it relates to transfer-level college courses, post-implementation. Significant keywords were used to filter the search results in online databases such as ProQuest, ERIC, Google Scholar, SAGE research methods, SAGE premier, Wiley, Taylor and Francis Group, and Research Gate.

Multiple Measures for Placement Criteria

The Community College Research Center was instrumental in researching the predictive validity of placement scores such as ACCUPLACER and Compass and compared it to High school GPA scores to determine which served as a better predictor of student outcomes. The research was conducted by Scott-Clayton et al. (2012) of CCRC and published two papers that showcased findings that stand-alone tests showed relatively low predictive validity when compared to HSGPA. However, when they combined the two measures (placement test and HSGPA) to form another placement score, that measure was an even better predictor of student success in transfer-level courses. When they combined four or more different measures, it made a “rich predictive placement algorithm” over two or three measures (p. 12). Besides, the combined measure could moderate the disproportionate impact (that is, negative impact) on specific student subgroups, such as Blacks and Latinos. Thus, the term “multiple measures” was popularized and gained nationwide attention and importance.

The default placement rule (as per AB 705 memo) and the decision band cutoff for HSGPA is provided in Appendix C and Appendix D for Statistics and Precalculus

courses. The recommended default placement rules by CCCCCO was a direct result of the MMAP decision tree analysis. Placement recommendations were formed based on the decision tree, a machine-learning algorithm (data modeling based on if-then rules), where the data created groups or nodes if the students met or exceeded a minimum average probability of success at a particular level. The goal was to identify students who were highly likely to succeed. However, to comply with AB 705, the research was modified to identify students who were highly unlikely to succeed when placed directly in a transfer-level course, to determine if their throughput success rate can be maximized without placing them in remedial courses. The focus was on the lowest high school performance, which corresponded to the lowest node.

The research showed findings that even students with HSGPA lower than 1.9 had a 43% predicted success rate in transfer-level English (MMAP Research Team, 2018, p. 7). The MMAP research team (2016) published a revised Phase II analysis by making changes to how the decision tree was grown. There were three key differences in the statistical application - 1) Phase I predicted grade points in a target college course, while Phase II predicted success rates, 2) Phase I used ANOVA-based classification and regression trees while Phase II used Poisson-based classification, and 3) in Phase I, each college-level was modeled independently while Phase II did it recursively (MMAP Research Team, 2016, p. 3).

The AB 705 implementation memorandum used the results based on the research conducted by the MMAP team in support of the AB 705 Implementation Advisory Committee. This research represented analysis from 2007-2014 on students who were placed using a placement test and correlated it to their HSGPA and success in class when

first enrolled. It indicated that direct placement into transfer-level English and/or mathematics/quantitative reasoning might best serve many students, particularly those who recently completed high school. Keeping throughput as the baseline metric, the decision tree analysis and consequent placement criteria using multiple measures of assessment (as in Appendix C and Appendix D) demonstrated that a higher percentage of students are more likely to successfully complete a transfer-level course in one year than the data from the cohort placed one level below (Hope & Stankas, 2018, p. 5). Long sequences also offer multiple exit points for students who fail a class or fail to register for the next class in a sequence (Bailey et al., 2010).

Predictive Validity

When measuring a particular criterion such as success in a critical course, the extent to which a score on that measure predicts that criterion is known as predictive validity (Belfield & Crosta, 2012; Hayward, 2017). In other words, a demonstration that a placement system is associated with course success rates is usually evaluated using a correlation coefficient (Hayward, 2017). This measure must show that there is statistical significance and should be robust enough to inform accurate placement decisions.

The MMAP research team (RP Group, 2014) recommended a predictive validity correlation range of 0.10 to 0.21 to be a typical observation. In the quest for finding the best predictor of success, validity tests on different testing/scoring instruments were performed. Some studies tested the validity of placement tests such as ACCUPLACER, Compass (which was discontinued in 2016), or ACT and SAT scores. Some others focused on High School GPA, while still, some others focused on other measures that included noncognitive variables, employability skills, and work experience. Based on

their meta-analysis results, Burton and Ramist (2001) reported that the average adjusted correlation of verbal and math SAT scores with cumulative college GPA was 0.36. It was compared to a correlation of 0.42 for high school grades with a college GPA. The College Board research by Kobrin et al. (2008) showed that the unadjusted correlation between the SAT and college grades was between 0.26 and 0.33. Hughes and Scott-Clayton (2011) found ACCUPLACER's predictive validity to be 0.10 to 0.13 for English and 0.23 to 0.25 for Math. McManus et al. (2013) used several post-secondary predictor-outcome combinations and found 0.17 as the average correlation.

While no correlation coefficient can be settled upon as an absolute indicator, retrospective data baseline results on the uncorrected statistical association showed that at least a correlation coefficient of 0.15 (i.e., $r \geq 0.15$) represented a reasonable guideline for predictive validity (California Community College Assessment Association, 2001). Multiple quantitative studies conducted by the Multiple Measures Assessment Project (MMAP) and California Acceleration Project (CAP) supported this baseline value using correlational and multivariate analysis. The 0.15 value is a recommended floor value to predict a later success of C or higher. However, if an instrument can show a predictive validity of 0.35 or higher, it should be considered a highly useful and robust predictor, taken as a whole to be the upper limit of observed predictive validity, as seen in the literature mentioned above.

As a general threshold for better applicability, the US Department of Labor (1999) produced a document outlining the utility of tests based on the strength of their predictive validity: (1) above 0.35—very beneficial, (2) 0.21 - 0.35—likely to be useful, (3) 0.11 - 0.20—depends on circumstances, and (4) below 0.11—unlikely to be useful.

However, the application of the tests and placement system will ultimately determine if a given correlation is useful or not, depending on whether the test is being utilized by itself or in combination with other measures.

Co-requisite Support

Reviewing the literature showed plenty of data that supported co-requisite remediation as a very effective instructional strategy in disciplines such as chemistry, mathematics, reading, sociology, and writing. Programs that included additional instructional support such as supplemental instruction, embedded tutor, lab component, or co-requisite support showed greater student success in transfer-level courses. Successful programs such as the English program at Community College Baltimore County, a mathematics program at Austin Peay State University, the FastStart program at Community College of Denver, and the Statway program by the Carnegie Foundation for the Advancement of Teaching are some of the examples where additional instructional support showed successful results in desired student outcomes. Many public colleges such as Bakersfield Community College, Long Beach College, Tulsa Community College, University of Central Arkansas, CUNY, Cuyamaca College, College of the Canyons, Chabot College, and Middlesex Community College, also tested their own corequisite models and reported dramatic success in completion rates.

The CUNY college performed a randomized controlled experiment that investigated the effects of co-requisite math remediation on student success in college-level statistics course (Logue et al., 2018). The study was a three-year follow-up to the one conducted by the same researchers in 2016 (Logue et al., 2016). This research started initially in 2013 and tracked three years of data on graduation rates. In general, CUNY

remediation data are typical of national data. The general CUNY data reflected the national data in that 76% of fall 2014 new CUNY community college first-year students were assessed as needing remedial mathematics. Only 38% of students in the highest-level (elementary algebra) fall 2014 CUNY remedial math course passed (Logue et al., 2018).

Randomized controlled experiments are considered as the gold standard in statistical research techniques that wish to study cause and effect. In an attempt to understand if the instructional support was genuinely useful, the CUNY researchers examined a promising approach for overcoming impediments in completing mathematics remediation courses (Bickerstaff & Edgecombe, 2019). In the initial study, students were randomly assigned in summer 2013 to the courses they would attend in fall 2013. The researchers randomly assigned 907 students to one of the three courses: (a) remedial elementary algebra, (b) that same course with workshops, or (c) college-level statistics with workshops (corequisite remediation). The experiment compared completion (pass rates) in remedial elementary algebra to college-level statistics course for students who were evaluated as needing remedial Elementary Algebra course.

Intent-to-treat (ITT) analysis and Treatment on Compliers (TOC) methods were used by the CUNY researchers to establish significant treatment effects on passing. To further investigate the predictors of participants' success in the assigned courses, the researchers utilized logistic regression. The study showed that students assigned to statistics passed 16 percentage points higher than algebra students ($p < .001$) and went on to accumulate more credits in subsequent courses. A majority (55.69 %) of enrolled statistics students passed the course (Logue et al., 2016).

At institutions with widespread co-requisite success, strong pathways implementation has been of fundamental importance. Co-requisite courses take different formats, namely, boot camps that are intense, extended hours each week with embedded support classes, separate but linked support courses that run throughout the semesters, mandatory tutoring or embedded tutoring, compressed courses, stretch courses, and other structures—all of which enable a student to complete a college-level course while receiving developmental mathematics support (Richardson & Dorsey, 2019). Structural considerations also include factors such as staffing, placement, and whether to have students co-mingle or be part of a cohort. Under the cohort co-requisite model, transfer-level courses are separate for the college-ready and the underprepared students who need additional support through co-requisite class, in one of the formats mentioned above (Richardson & Dorsey, 2019, p. 52). In the co-mingled co-requisite model, the transfer-level courses mix college-ready and underprepared students in the same main course while the underprepared students attend ongoing support outside the core course in one of the formats mentioned earlier.

The authors warned that attempting to scale up a pilot co-requisite course can sometimes reveal “inconvenient truths” that may have been ignored in the pilot development (Richardson & Dorsey, 2019, p. 48). Faculty interviews, based on the co-requisite instruction interview protocol employed by the authors, helped put together a recommendation for a comprehensive approach. One of the main considerations was in shifting the culture of the math department from “sink-or-swim” to “we’re all in this together” for successful programs, followed by a collaborative and transparent culture

where students are explicitly instructed about the purpose, benefits, and structure of the co-requisite model (Richardson & Dorsey, 2019).

Guided Pathways

Liston and Getz (2019) from the DANA Center for Mathematics Pathways at the University of Austin, Texas, presented their case for mathematics pathways. High-quality mathematics pathways can significantly increase student success by addressing three “structural barriers of the problem - (1) the inaccurate placement of students, mostly into math courses below their ability to perform, (2) the misalignment of content to student needs, and (3) long, multi-semester course sequences” (p. 1). Previously, students seeking a specific career path were left without direction due to misaligned pathways. The focus of the realigned math pathways and recent findings from associated studies (Fitzpatrick & Sovde, 2019; Leahy & Marshall, 2019) suggest overwhelming evidence of accelerated student completion of gateway transfer-level courses. Several states such as Tennessee and Virginia have reported improved mathematics success and completion rates from realigned, guided math pathways. The achievement gap in transfer-level courses was virtually eliminated when placed in guided pathways. Minority students showed 73% completion compared to 75% success for all students. Low-income students showed 72% completion while the overall success rate of minority students increased by seven times to 47.3% (Denley, 2016).

Quantitative studies on the Carnegie Mathematics Pathways showed evidence that students of color outperformed their counterparts in traditional mathematics course sequences (Huang & Yamada, 2017; Klipple, 2016). In their Statway and Quantway models for Statistics and Quantitative Reasoning transfer-level math courses, Black

students showed a success rate of 43% to 47% in the college-level mathematics courses versus their comparison group at 5% to 7%. The Latinos ranged from 36%-42% compared to those in traditional courses with success rates of 7% to 8% (Klippel, 2016). Additional data showed that Black females presented the most significant gain in mathematics achievement when compared to their baseline performance (Huang & Yamada, 2017). They also exhibited an overall positive effect on degree completion and credential attainment (Norman, 2017).

Hayward and Willet (2014) used logistic regression and multivariate models to analyze student outcomes from 16 CAP (California Acceleration Project) colleges offering redesigned English and mathematics pathways in 2011 and 2012. The study found that students at all levels showed higher throughput rates in accelerated pathways. CAP is part of the California Community Colleges Success Network (3CSN). CAP math colleges received training and guidance on two central tenets of the project. They were (1) creating a single transfer-level; and (2) incorporating backward design with intentional support affective domain needs (Hayward & Willett, 2014; Hern & Snell, 2010; Hern & Snell, 2014). In other words, CAP instructional design principles are encompassed in creating “high challenge – high support classrooms” (Hern & Snell, 2013). The study involved 2,489 students in an accelerated pathway, and the overall effect of the curricular redesign was robust and significant. Among the math colleges, the majority (7 of 8) of the accelerated math pathways showed significant acceleration effects with a large and statistically significant effect size of 4.0 (after removing a specific high outlier). The quantitative study showed that transfer-level math students’ odd of completion was 4.5 times greater in accelerated pathways (38% completion rate) than in

traditional sequence (12% completion rate) (Hayward & Willett, 2014). The study results were analyzed after controlling for demographic and academic variables. The positive results implicated that students from diverse backgrounds and an array of skill ranges can be prepared for success in transfer-level Mathematics through accelerated pathways.

The Dana Center Mathematics Pathways (DCMP) is focused on bringing systemic changes in higher education, including curriculum design, professional development, advising, institutional research, institutional and state policy alignment, and national advocacy, with a vision for equitable access, aligned programs of study, and opportunity for success in rigorous math pathways. A recent monograph published by DCMP provided a comprehensive analysis of mathematics pathways based on case studies, scans of the field, and recommendations for implementing mathematics pathways in local colleges. The monograph is a collection of chapters written by prominent leaders in the field and categorized into four sections. Some of the key chapters pertinent to this study combine emerging issues and critical perspectives on multiple measures for placement, designing co-requisite support, accelerating transfer-level courses, and preparing faculty through engagement and sustained change to dramatically increasing the number of students who complete math coursework aligned with their chosen program of study through guided pathways (Hartzler & Blair, 2019).

Peck (2019) argued that there is compelling evidence that underprepared students who chose the statistics pathway are far better served by being placed in an accelerated statistics pathway as it allows throughput completion in a single semester or within a one-year timeframe (p. 38). Success in mathematics is one of the biggest barriers to students' college completion (Complete College America, 2017). When compared to STEM

pathways, students in non-STEM (Statistics) pathways tend to show better throughput success since it is not algebra-intensive. For students who are interested in careers and programs of study that require intensive algebra, Fitzpatrick and Sovde (2019) recommended four steps for a seamless transition from high school to college by “(1) requiring four years of mathematics for high school graduation, (2) encouraging students to enroll in courses during all years of high school, (3) supporting all students in choosing which mathematics launch years courses to take based on their areas of academic, personal, and career interests, and (4) identifying students who are not ready for credit-bearing college mathematics by the end of their junior year and offering a twelfth-grade mathematics transition course” (p. 100).

Disproportionate Impact (DI) on Student Subgroups

According to California Community Colleges Chancellor’s Office (CCCCO), the term disproportionate impact (DI) is defined as a condition where inequitable practices may hinder the key access to resources and support for some students, policies, and approaches to student support, ultimately impeding their success (Harris, 2013; Harris, 2015). That is, when one student subgroup achieves an outcome such as degree completion at a rate that is substantially lower than the benchmark rate, that subgroup may be referred to as “disproportionately impacted” (Harris, 2013; Sosa, 2017).

Achievement gap or equity gap poses significant challenges to colleges all over the country, particularly in completion and degree achievement among underrepresented student populations (Bensimon, 2005). There is no dearth of research studies that point to inadequacies in educational outcomes, particularly among historically underrepresented groups (Harper et al., 2009; Ward, 2006). Research on incoming two-year college

students shows that only 33% complete the math sequence, and 20% complete the transfer-level math courses in three years (Bailey et al., 2010). These low outcomes affected the minority and underserved students adversely as they were most likely to be placed in remedial courses, consequently being disproportionately impacted by the high rates of failure.

To detect equity gaps and to be able to empirically measure the impact, there are three primary standard measures of DI, namely, the 80% rule, percentage gap method, and the proportionality index, that can be used to ascertain whether DI exists (Sosa, 2017). The Equal Employment Opportunity Commission (2007) defined the 80% rule as the ratio of the minority group placement or participation rate divided by the majority group placement or participation rate (Harris, 2013). If this ratio falls below 80%, evidence of disproportionate impact exists for the minority group. Colleges are encouraged to conduct campus research based on student equity success indicators. If a clear majority is not evident, then the overall placement or participation rate may be used as the reference rate (Glasnapp & Poggio, 2001). The percentage point gap approach to determining DI measures the difference in percentage points between a given demographic group's educational outcomes and the overall average (or mean) for those outcomes across all demographic groups (Harris, 2015). The proportionality index is measured when a group's representation with respect to one or more educational outcomes is found to be at a lower rate than its representation in the general student body, and disproportionate impact may be indicated (Harris, 2013).

In 2001, the Board of Governors in California identified five student equity success indicators for access, course completion, ESL and basic skills completion, degree

and certificate completion, and transfer that can be used to measure areas for which various population groups may be impacted by issues of equal opportunity and disproportionate impact (Harris, 2015). The IEPI (2016) study investigated disproportionate impact (DI) methods from three case studies – (1) DI among students applying but not enrolling, (2) DI in the context of course placements, and (3) DI among test takers. In a case study related to course placements, Sosa (2017) examined Fall 2015 data submitted by Riverside Community College District as part of their participation in the California Acceleration Project (CAP). The 80% index measure indicated that, with White students as the reference, the disproportionately impacted groups were African American (39.94%), Asian (73.08%), and Hispanic (53.06%) students. The point gap index measured the difference between the placement rate for all 3,411 students in the cohort (17.80% in this case) and each ethnic group. The index showed that African American students (-6.46 point gap) and Asian students (-3.48 point gap) were disproportionately impacted. The proportionality index indicated that African American students were identified as being disproportionally impacted. From the three different measures, one group stood out as being impacted the most, the African American students. In two of the three tests, Asian students showed a disproportionate impact as well. The finding suggested that institutions should develop strategies and implement them as a priority in narrowing the equity gap (Equal Employment Opportunity Commission, 2007; Harris, 2013; Harris, 2015; Sosa, 2017).

Throughput student success

As previously noted, throughput success rates refer to the percentage of students who successfully complete transfer-level Math courses with a grade of C or better within

the primary semesters of their first attempt in a one-year timeframe (MMA Research Team, 2018). The MMA Research Team (2018) published a detailed report on comparative throughput analysis for AB 705 compliance, disaggregating student populations by Disabled Students Programs and Services (DSPS) and Extended Opportunity Programs and Services (EOPS) status. One of the main objectives of the research was to determine any variance in throughput success rates in particular disciplines when placed directly in transfer-level courses versus one-level below transfer level. The research examined HSGPA ranges related to different levels of college performance determined by MMA decision trees (RP Group, 2014) for transfer-level English, Statistics, and Precalculus courses. The report scrutinized the percentage of students who completed the transfer-level courses in their first attempt with a grade C or better within two main semesters or three primary quarters and compared them across three ranges of high school performance based on the decision tree as seen in Appendix E (MMA Research Team, 2016).

The key findings indicated that EOPS students were one to two times more likely to complete transfer-level English; two to five times more likely to complete transfer-level Statistics; and improved their throughput by nearly 30 percentage points for transfer-level Precalculus, across all ranges of high school performance, instead of being placed one-level-below transfer-level. Similarly, DSPS students were one to three times more likely to complete transfer-level English and more than two times higher throughout when placed in transfer-level Statistics course than if they had started one-level-below transfer (MMA Research Team, 2018). Given the timeframe of the study from years 2007-2014, and the curricular structure and placement strategy employed during those

years, the analysis concluded that there was no evidence that students would have a higher throughput success rate by being placed in remedial, basic skills courses below transfer-level, whether based on high school performance or status such as DSPS or EOPS (MMAP Research Team, 2018).

Review of Methodological Issues

The studies that are reviewed herein focus on two broad topics, namely, placement criteria (encompassing remedial sequence of developmental courses, multiple measures for placement, placement test validity, and high school achievement data topics) and curricular redesign (encompassing accelerated courses, co-requisite support, guided pathways, and disproportionate impact on student subgroups among transfer-level mathematics students in California community colleges). The underlying theme for the review is related to factors that can maximize throughput student success, in the context of AB 705 California law.

Quantitative, qualitative, and mixed methods were used to examine AB 705 curricular reforms and AB 705 implementation for throughput student success. One of the main factors used extensively in the throughput success literature, pertaining to mathematics students, was the implementation of multiple measures for placement which uses high school grades to place most students directly into transfer-level courses with or without co-requisite support, thus bypassing remedial sequence of courses (Bailey et al., 2015; Bettinger & Long, 2009; Bickerstaff & Edgecombe, 2019; Hern & Snell, 2014; Hope & Stankas, 2018; MMAP Research Team, 2016; RP Group, 2014).

Quantitative

The review in this section pertains to the quantitative research on throughput student success in California community colleges. The strengths and weaknesses of qualitative studies, their results, and their conclusions examined in the previous section are reviewed to determine the factors that maximize throughput student success. A vast majority of the studies related to throughput success used quantitative methods.

Placement criteria

The ground-breaking research by Community College Research Center (CCRC) researchers, Judith Scott-Clayton, Peter M. Crosta, and Clive R. Belfield and the researchers at the Multiple Measures Assessment Project (MMAP) by the RPgroup, published papers in which they compared the placement of students based on the standardized placement test (ACCUPLACER, Compass) and their high school performance (GPA, high school level math courses) in order to determine the best predictor of student success. The significant findings from CCRC revealed that High school GPA was a better predictor of student success than a single placement test. HSGPA is a cumulative measure of the student's progress in courses over time, which also explains a student's noncognitive ability indirectly in sustaining through high school, while a standardized placement test measures a student's ability in the prerequisite knowledge over a few minutes.

However, the study tested the validity of creating a new placement score using both HSGPA and placement test and found it to be relatively higher than a single placement measure of HSGPA or only the placement test. When they tested the validity using four or more different measures, the predictive validity scores were significantly

higher than all other validity scores, indicating that multiple measures for placement produced the best estimator of student success. MMAP conducted a massive study based on more than one million students' college and high school records between 2007 and 2014 using CCCCCO's Management Information Systems (MIS) data mart. The study was a meta-analysis of data from high school grades up to college by reviewing the context, practice, and requirements about the use of multiple measures in accessing and placing students in California community colleges. The research explored the data using predictive models, derived from logistic regression and recursive partitioning and via decision tree procedures.

The MMAP research and studies conducted by Community College Research Center (CCRC) of Columbia University indicated that high school grades, particularly GPA, was the best predictor of student success in college-level courses and recommended that placement criteria be applied based on multiple measures of high school achievement. When reviewing then the MMAP projected results (Hayward & Willett, 2014) in light of AB 705 law implemented in all California community colleges, much variation is expected due to the fact that majority of the colleges at the time of study did not institute multiple measures of placement, guided pathways, or curricular redesigned curriculum. Therefore, mainstreaming the placement criteria so that it works for all students from all backgrounds without causing disproportionate impact could become quite challenging as confounding variables could not be singled out with certainty in studies that did not use randomized control experiments.

The concern with studies that lacked randomized, control design is that there could have been uncontrolled, unmeasured differences in some groups that were exposed

to the treatment that the control group may have not (as in some studies using propensity score matching) while some other findings may be limited to a narrow group (as in some studies using regression discontinuity) making it unlikely to be generalized across diverse student populations. Furthermore, there may be other emotional, psychological, or social interferences that may have affected their motivation and hence, the outcome (Acee et al., 2017; Nissim et al., 2016; Skinner et al., 2008).

Curricular Redesign

The Public Policy Institute of California (PPIC) published a statistical report in October 2017 on the students' outcomes from two refined pathways. For the study, the Statistics pathway and compressed math pathway were compared (Rodriguez et al., 2017). The statistics pathway showed substantially better outcomes (49% who completed the transfer-level courses versus 16% in traditional sequence) and picked up more transfer units (39 versus 27). The compressed math pathway showed somewhat better outcomes (28% who completed the transfer-level courses versus 15% in traditional sequence) with transfer units somewhat close to the statistics pathway (34 versus 27). According to the study, all student groups, including the underrepresented populations, showed overall better outcomes.

Among quantitative studies related to curricular redesign elements, such as accelerated courses, co-requisite support, and guided pathways, very few studies used the gold standard for research, namely, the randomized controlled trials (Edgecombe, Jaggars et al., 2013; Klipple, 2016; Logue et al., 2016). The studies that involved testing the validity of a new change in placement instruments used correlational analysis. Studies that involved meta-analysis of multi-college data mainly used logistic regression and

multivariate analysis when measuring throughput optimization via placement decision rules and decision tree analysis (Barnett et al., 2018; Belfield & Crosta, 2012; Bickerstaff & Edgecombe, 2019; CCCCO, 2019; Central Valley Math Pathways Task Force (CVMPTF), 2018; Hayward, 2017; Hayward & Willett, 2014; Hern & Snell, 2014; Kobrin et al., 2008; MMAP Research Team, 2018; PPIC Higher Education Center, 2016; Rodriguez et al., 2018).

The general conclusion from the findings of meta-analysis studies (CAP Central, 2018; Barnett et al., 2018; Belfield & Crosta, 2012; MMAP Research Team, 2018; RP Group, 2014) examining multiple measures for placement and curricular redesign shared common indicators of success such as placing directly in transfer-level courses using multiple measures of high school data, embedding co-requisite support in accelerated courses using just-in-time remediation pedagogical approach, and allowing students to choose their desired pathways (STEM or non-STEM) at the time of enrollment following a guided approach to throughput success.

Qualitative

The review in this section pertains to the qualitative research on throughput student success in California community colleges. The strengths and weaknesses of qualitative studies, their results, and their conclusions are examined and discussed to determine the most suitable practices for maximizing throughput student success.

Researchers who conducted studies using qualitative methods provided surveys, interviews, case studies, focus groups, surveys on affective domain qualities such as student engagement, motivation, persistence, grit, and growth mindset, best-practices on active learning methods, pedagogy, and recommendations on policy and reforms

(Bakersfield College, 2013; Central Valley Math Pathways Task Force (CVMPTF), 2018; Cuyamaca College, 2019; Duckworth, 2016; Dweck, 2006; Henson et al., 2017; Hern & Snell, 2014; Hern & Snell, 2013; Huntsman et al., 2016; Pappas, 2013; The CAPacity Gazette, 2019; Wiggins & McTighe, 2005; Xerri et al., 2018).

Other researchers produced monographs, reviews, toolkits, guides, compilations, executive summaries, and handbooks on student engagement, student success, and high-impact strategies and practices (CCCCO Scorecard, 2018; CCCCCO, 2019; Central Valley Higher Education Consortium, 2018; Central Valley Math Pathways Task Force (CVMPTF), 2018; Hanover Research Council, 2015; Kinzie & Kuh, 2016; National Center for Education Statistics, 2019; National Research Council, 2000; Trowler & Trowler, 2011). Educational writers who presented their reports in educational magazines, periodicals, and journals wrote mostly opinion pieces and placed their arguments based on the conversations and documents shared at conventions, conferences, and committees (Boylan & Goudas, 2012; Fain, 2013; Jones, 2014; Karp & Bork, 2012; Smith, 2019; Valbrun, 2018).

Placement Criteria

One of the main arguments in favor of multiple measures for placement is that such a move will place almost all students directly in the transfer-level course and skip remedial courses which were long seen as a barrier to college success (Barnett et al., 2018). Instead of remedial courses, co-requisite support courses are offered as a popular form of remediation that places students in college-level courses but gives them additional support (Smith, 2018). The Public Policy Institute of California (PPIC) found that a majority of students never took or completed transfer-level courses when they were

placed in a traditional remedial course based on a single placement test. Placement tests are shown to be weak predictors of students' performance in college as it does not take into account students' past achievements or readiness (Belfield & Crosta, 2012).

The publication, *Capacity Unleashed*, by California Acceleration Project (CAP) chronicles the stories of 13 students who participated in alternative math remediation at City College of San Francisco, Berkeley City College, College of the Canyons in Santa Clarita, and Cuyamaca College in the San Diego area (Huntsman et al., 2016). In the report, the participants expressed their individual circumstances that led them to college and how likely it would have been for them to have left college without a degree had they been placed in remedial classes. Their lived experiences provided a snapshot of different students' needs, backgrounds, preparedness, and priorities while they shared one common desire to finish college and earn a degree. They shared their success stories and owed it to their colleges for using alternative math remediation by placing them directly in transfer-level courses but with embedded support. In CAP's first newsletter, *CAPacity Gazette*, featured stories about colleges that were ahead in the implementation of AB 705. The success stories highlight students completed with excellent grades just because those institutions changed their placement system trusting that their students will be highly likely to succeed in transfer-level courses (The *CAPacity Gazette*, 2019).

A phenomenological study on the implications of placement testing among veterans in community college revealed their perceptions and experiences with college placement and remediation for college-level coursework (Robertson, 2019). The qualitative analysis of the participants' narratives showed common emergent themes on age, forgetfulness, misconceptions, developmental level, and adjustment where all

participants described experiencing a gap in time and loss of memory or prior knowledge. The focus groups and interview sessions with the 18 participants found that remediation was the typical outcome for veterans (all of them were placed in remediation) who had not engaged in formal academic pursuits, thus presenting a challenge when transitioning to college-level coursework. In this study, it was found that being placed in the remedial courses first was beneficial in getting adjusted to academic expectations, standards, and habits (Robertson, 2019).

Curricular Redesign

Curricular redesign indicates the reorganization of content, instruction, activities, and curriculum in order to facilitate the completion of course requirements in a higher education setting, particularly in community colleges (Deane et al., 2017; Fink & Jenkins, 2017; Jenkins & Fink, 2016; Wyner et al., 2016). The CUNY Start mathematics program described four features that differ from traditional developmental education, namely, “the use of a highly detailed curricular document as a primary resource for instructors; an emphasis on real-world contexts and number relationships, which serve as the instructional starting point (rather than rules and procedures); a pedagogical approach that elicits student talk and discussion through questioning; and explicit attention to students’ organizational and study skills” (Bickerstaff & Edgecombe, 2019, p. 1). The faculty teaching the redesigned courses are recommended to undergo professional development so as to “make necessary changes in structures, attitudes, paradigms, and strategies for student success by building on strengths of students, faculty, staff, and the institution” (Hanover Research Council, 2015, p. 12).

When developing guided pathways based on meta-majors, faculty conversations have fostered efforts towards the common goal of creating sustainable systemic change as required by AB 705. Faculty engagement has been vital to data analysis, identification of problems and solutions, design and implementation of those solutions, evaluation of progress, and understanding of changes accompanying the implementation of mathematics pathways (Michal & Oehrtman, 2019). It was evidenced that being engaged in accelerated guided pathways augmented the chances of students completing the gatekeeper/transfer-level course (Hayward & Willett, 2014; Hern & Snell, 2010; Hern & Snell, 2013; RP Group, 2018). Institutions that are implementing pathways, meta-majors, and multiple measures placement, along with the co-requisite models designed either as cohort model or co-mingled in order to best serve their student population and local context have improved benefits of aligned programs (Richardson & Dorsey, 2019). In addition, accelerated mathematics pathways increase student success in the first transfer-level mathematics course to 60% or more (compared to 20% in remedial sequence), less cost (from not paying tuition of two semesters or more) and in a much shorter timeframe (Hartzler & Blair, 2019).

The founders of the California Acceleration Project (CAP) have been supporting faculty-initiated pedagogical and instructional changes at the grassroots level in many local California colleges. The guiding principle for their curricular design is promoted through their slogan “High Challenge, High Support” (Hern & Snell, 2013). The piloting colleges showed a dramatic increase in student completion and success rates prompting the founders to follow-up with open, free materials that can be edited to meet the user college’s specific needs. The course is housed in Canvas, an educational platform for

Learning Management System (LMS) that most colleges use in California. Based on their years of working with faculty and CAP data, the free, class-tested materials for teaching college Statistics or Statistics with Corequisite Support includes free student workbook with 70+ class activities, labs and projects; an associated instructor's manual with full facilitation notes that utilize the CAP Curricular Design Principles; integrated activities, and strategies and tips for addressing the affective side of learning to keep students productively engaged (Henson et al., 2017; Hern & Snell, 2010; Hern & Snell, 2014; Huntsman et al., 2016).

Mixed Methods

The review in this section pertains to the quantitative and qualitative research on throughput student success in California community colleges. The strengths and weaknesses of mixed methods studies, their results, and their conclusions are examined and discussed to determine the most suitable metrics and practices for maximizing throughput student success.

Placement Criteria

In February 2019, the MMAP Research Team (2019) published a summary of results based on the AB 705 implementation survey administered in Fall 2018. The 16-item survey instrument was distributed to the California Community College (CCC) chief instructional officers via the Chancellor's Office Listserv, to which 104 out of the 114 colleges responded. The purpose of the survey was threefold – to collect and share the experiences of California Community College in implementing multiple measures for placement, to determine the level of support these colleges needed to meet AB 705

requirements, and finally to obtain data to inform the legislature of colleges' plans and actions to execute AB 705 (MMAP Team, 2019).

The survey produced descriptive data related to the itemized questions as well as copious qualitative information such as open-ended responses that were compiled theme-wise, namely, funding, and professional development, guidance and clarification, data and technology, and Other Needed Resources. The responses within each theme were synthesized separately for English, credit ESL, and math. The results were presented under four key areas; namely, current landscape and placement practices, aligning English and math to AB 705 requirements, student support for AB 705 implementation, and needs identified to support the field with aligning English and math to AB 705 requirements. The report was a compilation of the open-ended survey responses in a tabular form where the college responses can be tracked by theme as well as by survey item number. The report also showed extensive open-ended responses with the data disaggregated for each of the 16 questions in the instrument by each participating college.

In relation to the math assessment measure of the instrument, the survey results indicated that 27% of survey respondents (27 colleges) were currently using guided self-placement (GSP) to place students who did not know their high school GPA score. Survey data showed that 65% (35 colleges) of statistics courses and 57% (17 colleges) of pre-calculus courses are piloting the implementation of co-requisites, while 90% (108 colleges) of statistics courses and 80% (57 colleges) of pre-calculus courses plan to implement co-requisites (MMAP Team, 2019).

Curricular Redesign

FastStart was launched in 2005 by Community College of Denver as a compressed model that combined multiple semester-length courses into a single intensive semester course for developmental math education. Edgecombe et al. (2013) conducted a mixed-methods analysis of FastStart's math program where they examined student persistence, transfer, graduation, credit accumulation, and enrollment and performance in entry-level college courses (p. 4). FastStart faculty improved their pedagogy and course content to integrate academic and student support services into their classrooms. So, the report also studied instructional delivery and its relationship to math achievement under the FastStart program. The quantitative study compared the outcomes of FastStart students with a comparison group of non-FastStart students. Each student was tracked for three academic years subsequent to his or her FastStart semester (i.e., six long semesters and the three intervening summer semesters).

The FastStart students appeared to have slightly higher short-term persistence rates and credit accrual, and substantially higher developmental math completion, gatekeeper math enrollment, and gatekeeper math passing rates when compared to non-FastStart students. Regression analysis was performed to determine whether differences in student characteristics drove the persistence and pass rates by controlling for moderator variables such as demographic variables, exposure to student success courses, and case management. In the three-year follow-up period, it showed that nearly 22% of program students and 23% of comparison students also enrolled at other community colleges or four-year colleges. The quantitative analysis showed that there was a “correlation between acceleration and higher rates of enrolling in and passing college-

level math courses, but not with increased persistence or with increased accumulation of college-level credits” (Edgecombe et al., 2013, p. 1).

On the qualitative side of the research, the students were asked to provide their input on the effectiveness of the FastStart program and what they gained in their participation. Students stated that FastStart contributed indirectly to their academic and non-academic development, such as academic proficiency and behavior modifications (Edgecombe et al., 2013). Students described their classroom environments was made approachable in tangible ways. One of the outstanding experiences was to see their faculty dedication and how vested they were in their success. Notably, they reported that the physical layout of classrooms using round tables and rolling chairs created a configuration that facilitated collaborative work among peers as well as student-instructor interaction. Such a layout was especially productive when working in an accelerated format with long blocks of instructional time (Edgecombe, 2011). Physical infrastructure and layout of the classroom were reported to be a motivating factor and positive engagement in other studies too (Cheryan et al., 2014; Hill & Epps, 2010; Sanders, 2013; Talbert & Mor-Avi, 2019).

Synthesis of Research Findings

The policymakers legislated in California, under the AB 705 bill, that all California community colleges (CCC) must “maximize the probability that a student will enter and complete transfer-level coursework in English and math within a one-year timeframe and use, in the placement of students into English and math courses, one or more of the following: high school coursework, high school grades, and high school grade point average” (AB705 Student Success Act, 2017, para. 2). The AB 705

implementation memorandum cited MMAP findings as evidence for establishing the default placement rules and the projected success rates at each placement level.

Accordingly, all CCCs must come into compliance by Fall 2019 to implement the requirements, and if any innovations were made to existing curriculum, sequence, placement rules (see Appendix C and Appendix D), or other instructional reforms must show evidence of having met or exceeded the success rates projected by CCCCCO (Hope & Stankas, 2018).

Early adopters implemented the reforms, and their stunning findings fueled the conversation nationwide and in California. Research groups and initiatives such as CCRC, MMAP, CAP, Dana Center, PPIC, CAI, to name a few, presented evidence of marked improvement in throughput success rates when students were placed directly in transfer-level courses (with or without support based on placement rules) instead of starting at remedial courses below transfer level. Moreover, the findings showed that there was no significant disproportionate impact for students from different subgroups by ethnicity, gender, and those in student support programs such as DSPS or EOPS.

Multiple Measures for Placement

The literature on placement criteria showed strong evidence from multiple studies that placement decision rules had underplaced students in remedial, developmental math sequence consistently, generally several levels below transfer-level mathematics course as a requirement for college completion and transfer to a four-year university (Bailey et al., 2010; Bensimon, 2005; Calcagno & Long, 2008; California Community College Assessment Association, 2001; Hern & Snell, 2014; Jenkins & Cho, 2012; Kuh et al., 2007; PPIC Higher Education Center, 2016; RP Group, 2014; The Community College

Research Center, 2018). Placement models such as disjunctive or compensatory considered only one of the scores, either the placement test or HSGPA, whichever was higher. This model is frowned upon since multiple measures for placement taken together conjunctively (HSGPA and past course completion) was shown to be the best predictor of success (Barnett et al., 2018; Belfield & Crosta, 2012; Kuh et al., 2007; Hern & Snell, 2013; RP Group, 2014).

The memorandum released by CCCCO provided the default placement rule that colleges were encouraged to use as a minimum threshold for compliance (Hope & Stankas, 2018). The default placement rule released by the Chancellor's Office in a 2018 memo showed the placement criteria, band cut-off for HSGPA, and placement decisions to be followed. See Appendices C and D for the complete placement rules for the non-STEM pathway and STEM pathway. According to the default placement rule, all students will be placed directly into transfer-level courses, with or without support. There are three bands or levels in the placement rule. The top-level is students with high GPA, the middle level for those with average GPA, and the lowest level is for students with a low GPA. As an example, in the non-STEM pathway, high GPA of more than 3.0 will qualify those students to be directly placed in a transfer-level Statistics class without support class. The medium GPA band is for those who earned a GPA between 2.3 and 3.0 and the low GPA is any score below 2.3. Students who fall in these two lower levels will still be placed into transfer-level Statistics courses but are recommended additional support.

Students placed directly in a transfer-level Statistics course with HSGPA at least 3.0 showed 75% as the projected success rate, whereas those with HSGPA between 2.3 and 3.0 in a transfer-level statistics course with corequisite support projected the success

rate at 50% for and for HSGPA below 2.3 showed 29% (Hope & Stanskas, 2018).

According to the AB 705 memorandum, by Fall 2021, colleges testing placement decision rules different than the default placement rules set by CCCCCO must show that their throughput success rates either met or exceeded the default success rates in order to validate the changes (Hope & Stanskas, 2018).

Co-requisite Support

The guiding principle of the co-requisite model is to “meet students where they are academically and provide them with the content and strategies they need to succeed in their college-level courses” (Dana Center Mathematics Pathway, 2018, p. 2). To address issues that have for long adversely impacted developmental mathematics students, many institutions, owing to AB 705, have made structural and cultural changes to ensure that the number of students passing their first college-level mathematics course is maximized through co-requisite support models.

There is no single best model for corequisite support as local student needs play a critical role in determining the appropriate model that best serves the local context. Many institutions have found that separate but linked support courses work well for quantitative reasoning or statistics courses, but they have struggled with that structure for the STEM pathway, in which case they preferred to use the cohort model (Dana Center Mathematics Pathway, 2018). While some models may be popular than the other, to narrow the gap between instruction and support, the recommended guidelines for a robust model are: using existing campus supports (guided pathways, content and pedagogy redesign, pathways alignment, multiple measures placement, persistence initiatives (to develop a growth mindset or productive persistence); selecting a cohort or co-mingled model with

appropriate calendar structures (one-semester just-in-time support or pre-requisite support), credit hours and financing, and grades; back mapping co-requisite content from the outcomes of the transfer-level course; assessing cultural shifts (collaborative work, early alert systems and intervention, explicit instruction, and ongoing formative assessment); and ensuring continuous improvement through data collection and evaluation (Complete College America, 2014; Dana Center Mathematics Pathway, 2018).

In the CUNY study, the three-year follow-up conducted in 2018 answered several questions and scrutiny raised despite the randomized study done in 2016. The 2018 report verified the conclusions made in 2016 about the effectiveness of corequisite remediation. It also investigated other concerns in the three-year study, such as consistency in the results, performance gaps, performance in general education completion and other math-intensive majors, increase in graduation rates, employability for statistics students versus elementary algebra students, and cost of education. It was found that the students in statistics course with corequisite support outperformed the other groups, even among underrepresented populations (Logue et al., 2018).

Guided Pathways

Mathematics pathways enable students to take different paths through the math curriculum so that their learning is aligned to their programs of study and relevant to their careers (Liston & Getz, 2019). The three structural barriers for students entering into traditional college math programs are the inaccurate placement of students, mostly into math courses below their ability to perform; the misalignment of content to student needs; and long, multi-semester course sequences (Liston & Getz, 2019, p. 1). Clearly, the high failure rates are attributed to the misaligned structure and content, and not

faculty or students. By addressing the barriers, it was deemed that high-quality mathematics pathways can significantly maximize students' success.

Typically, two broad pathways leading to multiple meta-majors within each pathway are offered in community colleges, namely, the STEM pathway and the non-STEM pathway. It has been successfully argued that more and more students are likely to be successful in courses that are both relevant and rigorous. Well-designed mathematics pathways utilizing policies and structures informed by research (Cuyamaca College, 2019; Liston & Getz, 2019; Rodriguez et al., 2018) and shaped by the practice guidelines of major professional associations (Central Valley Math Pathways Task Force (CVMPTF), 2018; McWhirter, 2019) are necessary for alignment with programs of study. In multiple studies it was shown that underprepared students can be successful in college-level math courses at higher rates and in less time as compared to students in traditional developmental sequences with the greatest advance comes from one semester co-requisites (Bailey et al., 2010; California Acceleration Project, 2015; Complete College America, 2016; Logue et al., 2018).

The Dana Center for mathematics has done much groundwork in developing guided pathways and co-requisite remediation for corresponding meta-majors that most California community colleges have adopted (Rodriguez & Mejia, 2016; CVMPTF, 2018; Rodriguez et al., 2018). Dana Center reiterated pertinent recommendations that tie all the elements of this study in that the placement practices should use multiple measures, align to the content of math pathways, and based on evidence of effectiveness and underprepared students should be placed in accelerated pathways with a one-semester, co-requisite model as a default (Dana Center Mathematics Pathway, 2018).

Disproportionate Impact (DI) on Student Subgroups

According to the California Community Colleges Chancellor's Office (CCCCO), "disproportionate impact is a condition where some students' access to key resources and supports and ultimately their academic success may be hampered by inequitable practices, policies and approaches to student support" (Harris, 2013, p. 4). Since the condition affects both the access and success of students, it is important to determine any disproportionate impact in throughput student success and ensure that guided pathways and placement policies are designed to increase community college student access and success to all students (CCC Student Success Task Force, 2011). In 2013, the Chancellor's Office put out guides and provided templates so that colleges can conduct their local research, particularly the student support and student success programs (such as EOPS, DSPS, CalWorks), so that student subgroups that receive their services are not disproportionately impacted. The guide provides definitions and explanations on how to use the three measures of DI, namely, the 80% rule, the percentage gap rule, and the proportionality index rule. Among these, the 80% rule is the clearest benchmark to determine DI as it is based on simple mathematics.

To utilize the 80% rule, the subgroup with the highest rate of success, referred to as the "reference" group must be identified first. To do this, Then the cohort group (the subgroup being examined by age, gender, ethnicity, or another characteristic) is identified, and the group's success rate is determined. The 80% index is found by dividing the cohort group rate by the reference group rate. If the success rates of the cohort fall less than 80% of the reference group's success rate, then that cohort group is disproportionately impacted (Harris, 2013; Hayward, 2017; Sosa, 2017). It is important to

conduct DI analyses for throughput success rates and success rates impacting each placement level. To keep up with the current standards, predictive validity and throughput rate should be disaggregated by various student subgroups (ethnicity, gender, age, and disabled students programs and services (DSPS) status) to determine if any groups are being adversely impacted by the placement system (Hayward, 2017, p. 6).

Critique of Previous Literature

This section provides a critical analysis of existing literature pertaining to placement criteria using multiple measures, co-requisite support, guided pathways, disproportionate impact on student groups, predictive validity, and throughput student success. In the analysis, I have looked at the effects and effectiveness of some of eliminating remedial courses, the state recommended default placement rule, multiple measures, post-AB705 implementation, and methodology issues related to factors and experiences that can maximize throughput student success among transfer-level mathematics students in community colleges.

Effects of Eliminating Remedial Courses

It has been long established through past research that student engagement is key to learning gains and student achievement in higher education (Pascarella et al., 2010). However, closer inspection of the evidence suggests varied results (Boylan, 2014; Boylan & Goudas, 2012; Fain, 2013). For instance, some studies using regression discontinuity design (Calcagno & Long, 2008; Martorell & McFarlin, 2011) concluded from their findings that remediation in colleges was of questionable value. Such a conclusion, according to Boylan and Goudas (2012), is flawed because the study incorrectly assumed that “participation in remedial courses should result in participants performing better than

students who did not take them” (para. 3). However, the purpose of the remedial courses is not to outperform but to level the playing ground for the inadequately prepared students who would otherwise not be able to engage in college-level courses and be successful meaningfully. Boylan and Goudas (2012) claimed that these studies have been defectively used as the basis for reforms and policy enhancements in many institutions, even circulated among institutions as significant recommendations by Complete College America.

On the other hand, Bahr (2010), who studied the effects of remediation at 107 California community colleges using large samples, concluded that remedial programs were highly effective in resolving skill deficiencies. Some other practitioners and educational researchers reject the practice of eliminating developmental courses as a “knee jerk reform” as it does not truly address the lack of college-readiness (Boylan & Goudas, 2012; Fain, 2013; Klemenčič & Chirikov, 2015). They argued against the prevalent notion that course completion was synonymous with student success. Instead, a good grasp of math concepts, college readiness, and course completion should be the holistic indicators of student success (Goudas, 2017).

Weighing the findings from both sides, the practitioners admitted that there was no single solution to handling student underpreparedness. Although the research methods used were rigorous, it is possible that unobserved characteristics, such as student agency and other non-academic factors, could have strongly influenced the results (CCRC, 2014). Therefore, robust research such as a randomized, controlled experiment is needed to understand the confounding factors behind these conclusions.

Mixed Results for Default Placement Rule

The discrepancies in the state's default placement rule are that firstly, it accounts for only a single measure, the HSGPA, instead of considering multiple measures. Secondly, the students are recommended support instead of *requiring* support, which means they are exposed to the same content as a "college-ready" student and are given the option to use support. The students who enter the Statistics course, having skipped all remedial coursework, are then expected to integrate fully into the course with elective support. By making co-requisite support optional for underprepared students, math faculty cannot measure if the student had mastered the needed basic skills or not. The pedagogical challenges for faculty in running such classes can be numerous and draining as some students will be advanced while some others will need to be retaught basic skills, making it difficult for the instructor to move forward or keep pace with the curriculum.

Many practitioners, particularly in Central California, have argued that a majority of their students were not seeking a transfer to universities (MMAF Team, 2019). They were more likely interested in career technical fields, vocational certificates, or Associate degrees. In order to earn an Associate degree, such student goals simply require the completion of Intermediate Algebra courses (STEM or non-STEM), which is a pre-transfer level course in the mathematics sequence.

Some colleges have maintained that many students were quite underprepared and were not ready to be placed directly into transfer-level courses, even with co-requisite support (Fain, 2013; Smith, 2018). Since recommended support is listed as optional participation as opposed to required co-requisite support, students may not feel the need to take additional help or just-in-time remediation offered in these support classes.

Instead, they were more likely to drop out or withdraw from the course rather than persist and complete. Also, students' plans change according to their circumstances. Students who once wanted to transfer may change their plans to settle for an associate degree or vice versa. Therefore, the default placement rule will not be suitable to apply the way it is, as it does not provide an option to place students in a pre-transfer-level course or to require co-requisite support. The default placement rule may need to accommodate two significant changes. It must require mandatory co-requisite support and place the lowest level students into a pre-transfer-level course.

Interpreting Multiple Measures

When it comes to multiple measures for placement, Goudas (2017) argued that misapplication of the findings and improper implementation might adversely affect thousands of students being placed in remedial courses or college-level courses. Goudas (2017) warned that it was the beginning of the shift from “multiple measures” to “multiple single measures” because the authors began to recommend that either “multiple measures” (i.e., a placement test in combination with HSGPA), or HSGPA alone, should be used to place students into or out of remediation, and to address disproportionate impact, a waiver system was recommended (p. 4).

The term multiple measures gave room to many alternative placement methods that colleges chose to use in their placement decisions as either compensatory or disjunctive (i.e., test scores or HSGPA *or* past math course) and some others used the conjunctive placement (i.e., test scores and HSGPA *and* prior math courses and other noncognitive tests). This disparity, Goudas (2017) said, had already caused damage to students placed in transfer-level or remedial courses instead of correcting severe

overplacement and underplacement issues. He warned that most policymakers were confused and not reading the study carefully before making legislative decisions because of the conflicting standards in the placement policy littered with several exceptions to accommodate any impacted subgroup.

For instance, when the papers on the effectiveness of multiple measures for placement by CCRC (Belfield & Crosta, 2012) got published in a national bureau in subsequent years (2012; 2014), their recommendation was not rightly promoted, and many institutions chose to apply only HSGPA as the placement criteria with a 2.6 cutoff (since it was equivalent to a B minus), as it was determined to be the single best predictor of student success in college-level courses according to the CCRC working papers. Some other researchers in CCRC supported this understanding since using HSGPA was not to be considered as a single score, rather an accumulation of a student's cognitive and noncognitive grades over time instead of a few minutes at the placement test.

Post-AB 705 Implementation

Multiple studies have established that student success rates could be maximized by reassessing the placement rules (Bailey et al., 2015; Barnett et al., 2018; Belfield & Crosta, 2012; Bettinger & Long, 2009; Boatman, 2012; Hayward & Willett, 2014; MMAP Research Team, 2018; Rodriguez et al., 2018). By doing so, the majority of the students will be placed in college-level courses, paving way for a shorter timeframe to complete college. While most results pertaining to placement were mostly encouraging, the findings could not be generalized for mainstreaming.

In some cases, the placement decisions were applied to self-reported GPA scores, which threatened internal validity as to whether the scores were inflated from the

original. Some other groups have argued that students tend to underreport their GPA for fear of being overplaced. Given the AB 705 requirements, the students have the right to be placed in the transfer-level course with support if they feel inadequate about their preparedness. Hence, the self-reported GPA is not of a major concern anymore. However, best practices for guided self-placement are being explored (MMAP Team, 2019). The fact that AB 705 allowed for colleges to experiment with their innovations while keeping with the minimum required compliance (Hope & Stankas, 2018) showed that it can be expected that there will be varied results emerging from the execution of these changes.

The most recent implementation survey conducted by the MMAP team identified several areas of weak implementation (that is, colleges with a substantial share of remedial courses in their schedules) that will need further attention from the colleges, the California Community Colleges Chancellor's Office (CCCCO), and possibly the legislature (Hern, 2019). However, it cannot be dismissed entirely as weak implementation either because many colleges that have diverged from the state's default placement rule are testing the changes and actively collecting data for validation (Hope & Stankas, 2018; MMAP Team, 2019; MMAP Team, 2019).

The predicted success rates in the default placement rule for transfer-level Statistics course indicated that the students with high GPA were expected to have a success rate of 75%, medium GPA of 50%, and low GPA of 29% (Hope & Stankas, 2018, pp. 6-7). In other words, these predicted rates were dramatically better compared to the current overall success rate of 10% for central California (Central Valley Higher Education Consortium, 2018) and 14% for all of California (CCCCO Scorecard, 2018).

However, it is yet to be determined if these numbers work in reality when the curricular reforms are validated post-AB 705 implementation.

Methodology

The literature review on the curricular reforms in developmental education happening nationwide as well as in California revealed that much-needed changes are being implemented by redesigning curriculum (corequisites support in transfer-level courses), guided pathways (focused completion), and multiple measures for placement (a better predictor of student success). However, most of the research studies did not explicitly include the conceptual or theoretical framework that guided their research. When conducting a literature review, it is important to narrow the scope of the topic to align with the conceptual framework. It would have been much more meaningful to critique the literature if the conceptual framework were presented in the studies related to AB 705 reforms and student success.

The studies that used quasi-experimental methods used the existing data obtained from course placement. When attempting to compare the performance of students as a way of assessing the need for remedial courses, the comparison often was between students who were directly placed in the transfer-level course and those who were placed first in remedial classes. The assignment of subjects was already a result of naturally occurring variation, so the variables could not be manipulated as in truly randomized control design. The most common statistical methods used in quasi-experimental methods were propensity score matching and regression discontinuity, producing mixed results. Some studies found that students needing remediation performed better if they first took remedial courses (Bettinger & Long, 2009; Moss et al., 2014). Some others

found that students performed better when they skipped remedial classes and were placed directly in transfer-level classes (Boatman, 2012; Calcagno & Long, 2008; Clotfelter et al., 2015; Jaggars et al., 2015; Martorell & McFarlin, 2011). Nevertheless, a few others found both these results to work based on the setting and student needs (Melguizo et al., 2011; Wolfle & Williams, 2014).

The qualitative studies based on case studies and narrative inquiry usually targeted a small number of students, such as 15-20, through one-on-one interviews, focus groups, and observations. These students were drawn from a single college or a single program and used their experiences to develop phenomenological or ethnographical sketches. In some other studies, the findings, though valid for a narrow group of students, may not be generalized for the general population. Unfortunately, the findings suggested based on these studies could not be considered scalable or transferable, even though valuable input was obtained from the research.

Summary

The extant literature on throughput student success rates provided extensive research on quantitative studies; however, there were not many qualitative studies conducted in this area. It is understandable because the focus is narrowed to the numerical metric of student success as in completion and success rates. However, when the literature search was expanded to student success and student engagement, the significant qualitative studies revealed the multi-dimensional quality of the construct – student success. Defining the term or construct - student success – has become an essential undertaking in many higher education studies. Many initiatives were launched

to study and understand the underpinnings of student success, which lead to investigating other dimensions of student effort and student agency.

The literature review offered a plethora of findings related to the initiatives and massive changes occurring throughout the nation to correct the issue of low completion rates. Community colleges are engaged in serious discussions about how to bring about reforms and increase student success and completion rates. Research teams such as MMAP, PPIC, CAP, and CCRC pioneered the multiple measures placement initiative. Their influential reports showed that students fared much better in transfer-level courses rather than when placed in a scaffolded sequence of remedial courses. Since the implementation of AB 705 in Fall 2019, incessant efforts are in place to monitor and survey the needs identified to support colleges throughout the process. The literature review in Chapter 2 has made clear the need for further research in the effectiveness of the revised placement rules for maximizing throughput student success.

CHAPTER THREE: METHODOLOGY

In this chapter, the focus was on the methodology employed in the study. The chapter has an introduction and purpose of the study. The research questions and the hypotheses arising from the research questions framed the focus of the study. The research design followed the pertinent background details of the study, such as the target population, sampling method, instrumentation, and data collection procedures. Data analysis procedures were explained with considerations on internal and external validity. Finally, the limitations and delimitations, as well as ethical issues in the context of the study, were discussed.

Research Questions and Hypotheses

Research Question 1

How does the throughput success rate in STEM and non-STEM pathways compare with those of the predicted baseline metrics set by the California Community Colleges Chancellor's Office (CCCCO)?

Hypotheses for Research Question 1

H₀: There is not a statistically significant difference between the observed throughput success rates and the predicted success rates for STEM pathway and non-STEM pathway.

H_A: There is a statistically significant difference between the observed throughput success rates and the predicted success rates for STEM pathway and non-STEM pathway.

Research Question 2

To what extent, if any, does a significant difference exist in the throughput grades among those who started at one of the three placement levels?

Hypotheses for Research Question 2

H₀: There is not a statistically significant difference in the throughput grades by the three levels of placement.

H_A: There is a statistically significant difference in the throughput grades by the three levels of placement.

Research Question 3

To what extent, if any, does a significant difference exist in the proportions of throughput success rates for Fall 2019 and Spring 2020 among student categories disaggregated by age, gender, ethnicity, DSPS, status, EOPS status, CalWorks status, and pathway choice?

Hypotheses for Research Question 3

H₀: There is not a statistically significant difference in the proportions of throughput success rates for Fall 2019 and Spring 2020 by the student categories.

H_A: There is a statistically significant difference in the proportions of throughput success rates for Fall 2019 and Spring 2020 by the student categories.

Method

The research study was based on a postpositivist worldview. This paradigm was useful for theory verification using empirical measurements (Creswell, 2014). For this study, the methodology utilized a quantitative approach using the causal-comparative research design (Brewer & Kubn, 2010). The data was obtained through a secondary source using archival data from the college district's database to study the influence of placement levels on throughput student success. In the past decade, researchers had shown in multiple studies that a correlational relationship existed between placement and

student success (Barnett et al., 2018; Belfield & Crosta, 2012; Bettinger & Long, 2009; Scott-Clayton et al., 2012). However, to establish that a cause-and-effect relationship exists between the placement level and throughput student success, Salkind (2012) stated that the order of occurrence of the variables could partly explain which variable influenced the other. Hence, studying the difference in the throughput rates based on the placement levels was a natural follow-up to the established relationship between the two.

Research Design Overview

The causal-comparative design was the most suitable research design as my study was non-experimental and involved effects on groups rather than individuals, with data obtained from past archival sources (Shadish & Galindo, 2010). I chose this design because it looked at existing conditions, analyzed the distinct independent and dependent variables with no direct manipulation of the independent variable, and it allowed the comparison of at least two populations (Brewer & Kubn, 2010). In a causal-comparative design, the independent variable cannot be manipulated in order to observe their effects because the event had already occurred (Silva, 2012). Observation of facts and examination of the outcome naturally occurred without my interference as the researcher. The pre-existing differences in the groups of individuals were studied retrospectively to determine the possible cause (Marsh & Gibson, 2018).

In this causal-comparative quantitative study, the dependent variable was the throughput success rates of mathematics students, and the independent variable was the placement levels with three groups, namely those starting directly at the transfer-level course with no required support class (Placement Level 1 - *Direct*), those starting at the

transfer-level course with mandatory co-requisite support (Placement Level 2 - *Coreq*), and those starting at a pre-transfer level course (Placement Level 3 - *Pretransfer*).

Participants

All mathematics students from community colleges in central California who were headed towards transfer-level courses in the academic year 2019-2020 formed the population for this study. Each cohort was tracked to determine their throughput grade to ensure that they entered and completed the transfer-level course. If a student was placed in a pretransfer-level course who was headed to a transfer-level course, then such cohorts were tracked from term to term and their student information was included in the data. To respond to research question 1, the population consisting of 3030 throughput student datasets were analyzed, out of which 524 were STEM students and 2506 were non-STEM students. The throughput rates from each guided pathway and corresponding placement levels were compared with the predicted baseline metrics given by the State (see Appendices C and D). The comparison was also performed by terms, with 1612 student datasets from Fall 2019 versus 1418 from Spring 2020. For research questions 2 and 3, the population was divided into three placement groups and a randomizer software (Urbaniak & Plous, 2017) was used to randomly select 100 students from the population for each placement level, thus accounting for 300 student datasets in the sample under study. This included cohorts from the academic year 2019-2020. The student records were obtained from the archival source that included corresponding demographic information (such as age, ethnicity, gender, EOPS status, DSPS status, CalWorks status) and pathway selection.

Data Collection

The data used in this study came from a secondary source of archival data stored securely in the management system database storage used by the college district. The system stores archival records of student placement and enrollment that includes information on high school GPA, completion of past math courses, enrollment data, status of math courses completed at the participating college, semesters enrolled, courses taken, including course levels; credits attempted and earned; and course grades, continuation of enrollment and completion from pre-transfer-level to transfer-level, guided math pathway selection into STEM or non-STEM, as well as demographic data on age, ethnicity, gender, EOPS status, DSPS status, and CalWorks status.

Data Collection Procedures

The quantitative data was obtained from the college district as secondary, archival data of mathematics students data sets from Fall 2018 until Spring 2020. The IRB approval was obtained from Creighton University and the participating college district before securing access to data. It was agreed in the approval that the college district will remove all identifying student information found in the shared database. The data was shared with daintified information and was stored securely in a password-protected file. Three years after the research has ended, the data will be purged from the system.

Data Collection Tools

One of the main reasons to conduct a quantitative study was to be able to provide robust evidence of the difference between variables. It was imperative to ensure that all aspects of the study were considered to reduce threats to internal and external validity so that the resulting findings are useful and valid.

Internal validity. Internal validity is used to identify any extraneous variables that may contribute to or distort the effect of the independent variable on the dependent variables (Shadish & Galindo, 2010). Threats to internal validity in a causal-comparative design are as follows:

Selection bias. The causal-comparative design is ex post facto, indicating that the study is done ‘after the fact.’ It was difficult to find out the similarity between groups when the event had already taken place via non-random assignment (Handley et al., 2018). To mitigate this threat, the randomizer software helped create random subgroups based on the independent variable (placement levels) to reduce variability (Urbaniak & Plous, 2017). Moreover, the archival data was received from the college district after de-identifying personal information about the students. Therefore, there was no threat of selection bias.

Instrumentation threats. The threat here refers to the measurement of the dependent variable, the throughput success rate. The data on throughput rates was obtained from archived sources. The data was provided as a categorical variable (letter grades) which required use of non-parametric tests which is considered less robust than parametric test. Another instrumentation threat was the inability to monitor if students were correctly placed into the starting courses as per the revised placement criteria. Since the placement criteria took into account multiple measures and not a single measure, it is believed that this process mitigated any threat of instrumentation.

Maturation and attrition threats. The maturation threat comes from the possibility where one group might mature differently than the other. For example, it could be that one group received a different teaching technique or the students simply

became more experienced, bored, tired, or disengaged in the course (Handley et al., 2018). In Spring 2020, the COVID-19 pandemic caused a worldwide health crisis which continued to last for several months. The impact of the pandemic on the students enrolled in the Spring 2020 semester may have caused maturation and attrition threats. The disaggregated information, including the drop percentages by placement levels and terms are provided in Appendices E, F, G, and H.

External validity. External validity is concerned with the ability to generalize findings from the study and to apply them outside the scope of the study parameters (Shadish & Galindo, 2010). Threats to external validity in a causal-comparative design are as follows:

Non-randomness. The threat that non-random assignment used in a causal-comparative design could introduce is the unintended effect of extraneous variables (variables that are not the focus of the study, but can confuse when interpreting the difference in the treatment effects) thus impacting the findings negatively (Brewer & Kubn, 2010). For this reason, sometimes, the generalization of findings may not be seen as useful when compared to true, randomized experimental design (Slavin, 2003). However, by creating homogenous subgroups, the effect of the confounding variable can be controlled. In this study, the equal samples were drawn from each placement level.

Sample size. In order to control for extraneous variables and make the study stronger, homogenous groups were created from the sample. It lowered the number of participants in the study and therefore limited the generalizability of the study (Brewer & Kubn, 2010). In a retrospective study, there is no threat of maturation or attrition. However, the pandemic, among other factors, could have impacted since attrition resulted

in smaller sample size for the *Pretransfer* level subgroup. To mitigate the effect, where necessary, the subgroups were combined to form larger samples and suitable statistical techniques (non-parametric or combining multiple variables as appropriate) were utilized.

Data Analysis

For research question 1, I used Microsoft Excel to sort the data variables using appropriate filters to extract the information needed. I filtered the data by the academic year 2019-2020 which included combined data from Fall 2019 and Spring 2020. There was a total of 3030 student records that were extracted, out of which 524 belonged to STEM pathway and 2506 belonged to non-STEM pathway. The throughput scores were made available as letter grades instead of percentage scores. Therefore, letter grades A, B, C, and P (if any) were filtered to obtain the count of those who passed successfully and divided by the total number of students in the cohort (observed throughput success rate). Similarly, letter grades D, F, NP, FW, and EW (if any) were filtered to obtain the count of those who did not complete successfully. This was done for each pathway, namely the STEM and non-STEM. Then, using the predicted success rates provided under the default placement in Appendices C and D, comparisons were made between the observed throughput success rates and predicted success rates for STEM pathway and for non-STEM pathway. To reveal further differences (if any), the same dataset was split by terms – Fall 2019 and Spring 2020 and by pathways – STEM and non-STEM, and similar comparisons were made. The descriptive statistics were provided as well as two-proportion z -tests were performed for each pair of comparison proportions to determine any statistically significant differences in the throughput success rates.

For research question 2, the data of 3030 student records were filtered to obtain random subgroups. Ethnicity was the only pertinent information was found missing in some student records. While in Appendices E, F, G, and H, the information for unknown ethnicity is provided, the sample for research question two had datasets with missing pertinent student information removed. For each placement level, 100 random student datasets were extracted using the randomizer software (Urbaniak & Plous, 2017) for a total sample size of 300. The data contained one dependent variable (throughput grades) that was measured at the ordinal level (letter grades). There was one independent variable (placement levels) that consists of three categorical, independent groups (Level 1 – *Direct*, Level 2 – *Coreq*, and Level 3 – *Pretransfer*). The independence of observations was verified so that there were different participants in each group with no participant being in more than one group (Laerd Statistics, 2017). Each student record contained the following variables and their corresponding levels of measurement were noted as follows: throughput grade (ordinal), placement level (ordinal), pathway (nominal), term (nominal), age (scale), gender (nominal), ethnicity (nominal), DSPS (nominal), EOPS (nominal), and CalWORKs (nominal).

Given that the dependent variable was ordinal (not continuous scale), a non-parametric test, the Kruskal-Wallis test was applied to determine whether throughput grades were different between placement levels based on the use of mean ranks to describe the group differences. Where statistical significance was found, follow up post hoc tests (pairwise comparisons) were performed. For disaggregated data, the throughput grade versus placement levels were filtered by the following categories based on the highest frequency of occurrence as per the descriptive statistics: Age: 25 years and below,

Gender: Female, Ethnicity: Hispanic/Latino, DSPS, EOPS, CalWORKs, and Pathway: Non-STEM. Kruskal-Wallis rank sum test was applied and post hoc test were followed up whenever appropriate.

For research question 3, the same sample from research question 2 was used to split the sample size of 300 into two subgroups by terms, namely Fall 2019 and Spring 2020. The dependent variable (throughput grade) was sorted by those who successfully completed the transfer-level course from whatever placement level they started to obtain results for throughput success only. Out of the 300 students in the sample, 148 successfully completed their transfer-level mathematics course, irrespective of their placement level or pathway choice. There were 84 students in Fall 2019 and 64 students in Spring 2020. The descriptive statistics were provided for Fall 2019 versus Spring 2020. Two-proportion z-tests were performed for each pair of comparison proportions to determine any statistically significant differences in the throughput success rates by the disaggregated data. Two proportions z-test for the difference in successful completion between Fall 2019 and Spring 2020 terms were determined for the following disaggregated categories: Age: 25 years and below, Gender: Female, Ethnicity: Hispanic/Latino, DSPS, EOPS, CalWORKs, and Pathway: Non-STEM.

SPSS software and Microsoft Excel spreadsheet were used for data analysis. Intellectus Statistics and Laerd Statistics tutorials were used for data interpretation.

Ethical Considerations

For this quantitative, retrospective causal-comparative study, the data was obtained from a secondary source stored securely in the college district's information database archives. Permission to use archival data was duly and ethically obtained before

beginning the research. Approval was obtained by following the prescribed procedures and protocols, as explained in the IRB instructions. The secondary data was securely transferred to a password-protected data file. Even though the process of obtaining secondary data is relatively straightforward, saves time, money, and resources, there is still a need for careful, ethical considerations as it involves human subjects (Tripathy, 2013). It is essential to store the data in a secure system (laptop or USB drive) that is intentionally encrypted to avoid unauthorized access.

The main concern with secondary data was the potential threat of divulging student information and other identifying facts. By removing personal student information and instead assigning generic, numerical identifiers, the identity and privacy of student information is not compromised. It is an ethical requirement, particularly in secondary data, to guarantee the anonymity of the subjects, so there was no need to obtain consent from the participants.

Nevertheless, it is generally advisable not to store sensitive data on the cloud as there is a possibility to retrieve from the server later, much after the physical copies are deleted. However, since the data in this study was received *after* all the identifying sensitive information were removed by the district, the risk is eliminated, if not minimized. Also, ethical considerations must be given when procuring the data, which was not collected initially to answer the present research question. Therefore, when conducting the research, it is an ethical responsibility to ensure that further analysis of the original data, now as secondary data is appropriate (Tripathy, 2013).

Summary

The data analysis was performed based on the nature of data information available. For instance, the throughput grades were made available as letter grades instead of percentage scores which required me to adjust the statistical techniques accordingly from ANOVA to its non-parametric version, Kurskal-Wallis. In order to mitigate, as much as possible, the impact of the pandemic on the data for Spring 2020, the research questions were developed in such a way so as to triangulate the results from different views and filters (such as academic year view versus the semester term view, STEM versus non-STEM filters, disaggregated data filters, and so on). Descriptive statistics were considered for frequencies and counts while suitable statistical techniques such as parametric tests (two proportions z -test) as well as non-parametric tests (Kruskal-Wallis test) were considered for data analysis.

CHAPTER FOUR: RESULTS AND FINDINGS

When performing the data analysis, the process involved examining the student datasets for any missing student records pertinent to the study and to ensure that the information in the pertinent fields were complete. The results section provides a complete description of the study results, followed by the discussion section where the results are explained in more detail.

Results

In this section, I have presented the tables and figures related to the research questions based on the study data.

Table 1 displays the throughput success rates of transfer-level mathematics students enrolled 2019-2020 academic year in the STEM pathway while Table 2 shows the corresponding information for the non-STEM pathway. The observed throughput is compared with the projected success rates provided by the Chancellor's Office for colleges to use as baseline metrics to validate the local throughput rates. The local placement rules are provided in Appendices A and B. The baseline data is provided in detail in Appendices C and D.

Table 1*Throughput Success Rates of Mathematics Students in STEM pathway*

		Placement Level 1 ^a		Placement Level 2 ^b		Placement Level 3 ^c	
		(Direct)		(Coreq)		(Pretransfer)	
		Success Rate	N	Success Rate	N	Success Rate	N
Observed throughput	2019-2020	36.8%	351	48.5%	169	75.0%	4
Baseline throughput	Predicted Success Rate	75%		53%		28%	

Note. N provides the count of the cohort in 2019-2020

- a. Starting at transfer-level with no support course
- b. Starting at transfer-level with mandatory corequisite support course
- c. Starting one level below transfer-level

Table 2*Throughput Success Rates of Mathematics Students in Non-STEM pathway*

		Placement Level 1 ^a		Placement Level 2 ^b		Placement Level 3 ^c	
		(Direct)		(Coreq)		(Pretransfer)	
		Success Rate	N	Success Rate	N	Success Rate	N
Observed throughput	2019-2020	45.2%	1718	41.6%	664	38.7%	124
Baseline throughput	Predicted Success Rate	75%		50%		29%	

Note. N provides the count of the cohort in 2019-2020

- a. Starting at transfer-level with no support course
- b. Starting at transfer-level with mandatory corequisite support course
- c. Starting one level below transfer-level

Table 3 shows the throughput success rates of transfer-level mathematics students enrolled in Fall 2019 and Spring 2020 in the STEM pathway while Table 4 shows the corresponding information for the non-STEM pathway. The observed throughput is compared with the projected success rates provided by the Chancellor’s Office for colleges to use as baseline metrics to validate the local throughput rates. The local placement rules are provided in Appendices A and B. The baseline data is provided in detail in Appendices C and D.

Table 3

Throughput Success Rates of Mathematics Students in STEM pathway by term

		Placement Level 1 ^a		Placement Level 2 ^b		Placement Level 3 ^c	
		(Direct)		(Coreq)		(Pretransfer)	
		Success Rate	N	Success Rate	N	Success Rate	N
Observed throughput	Fall 2019	34.3%	175	55.0%	100	100.0%	3
	Spring 2020	39.2%	176	39.1%	69	0.0%	1
Baseline throughput	Predicted Success Rate	75%		53%		28%	

Note. N provides the count of the cohort split by term

- a. Starting at transfer-level with no support course
- b. Starting at transfer-level with mandatory corequisite support course
- c. Starting one level below transfer-level

Table 4*Throughput Success Rates of Mathematics Students in non-STEM pathway by term*

		Placement Level 1 ^a		Placement Level 2 ^b		Placement Level 3 ^c	
		(Direct)		(Coreq)		(Pretransfer)	
		Success Rate	N	Success Rate	N	Success Rate	N
Observed throughput	Fall 2019	42.6%	895	41.4%	345	48.9%	94
	Spring 2020	48.1%	823	41.7%	319	6.7%	30
Baseline throughput	Predicted Success Rate	75%		50%		29%	

Note. N provides the count of the cohort split by term

- a. Starting at transfer-level with no support course
- b. Starting at transfer-level with mandatory corequisite support course
- c. Starting one level below transfer-level

Figures 2 and 3 below provide the bar graphs for Tables 1 through 4. The bar graphs are provided for the throughput success rates of STEM and non-STEM students when compared with the baseline metrics.

Figure 2

Throughput Success Rates for STEM Pathway

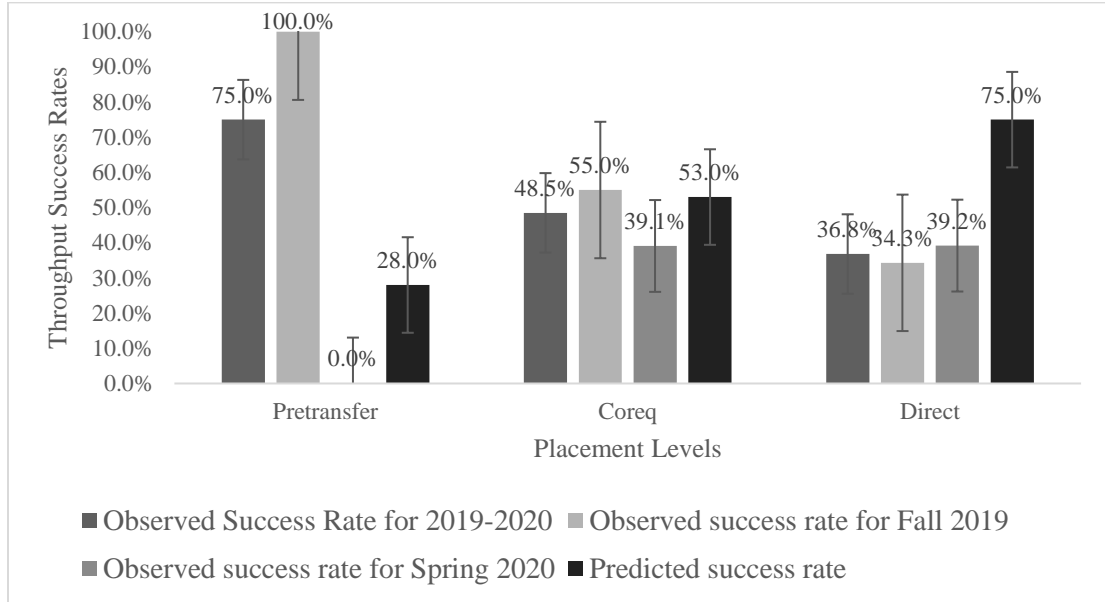
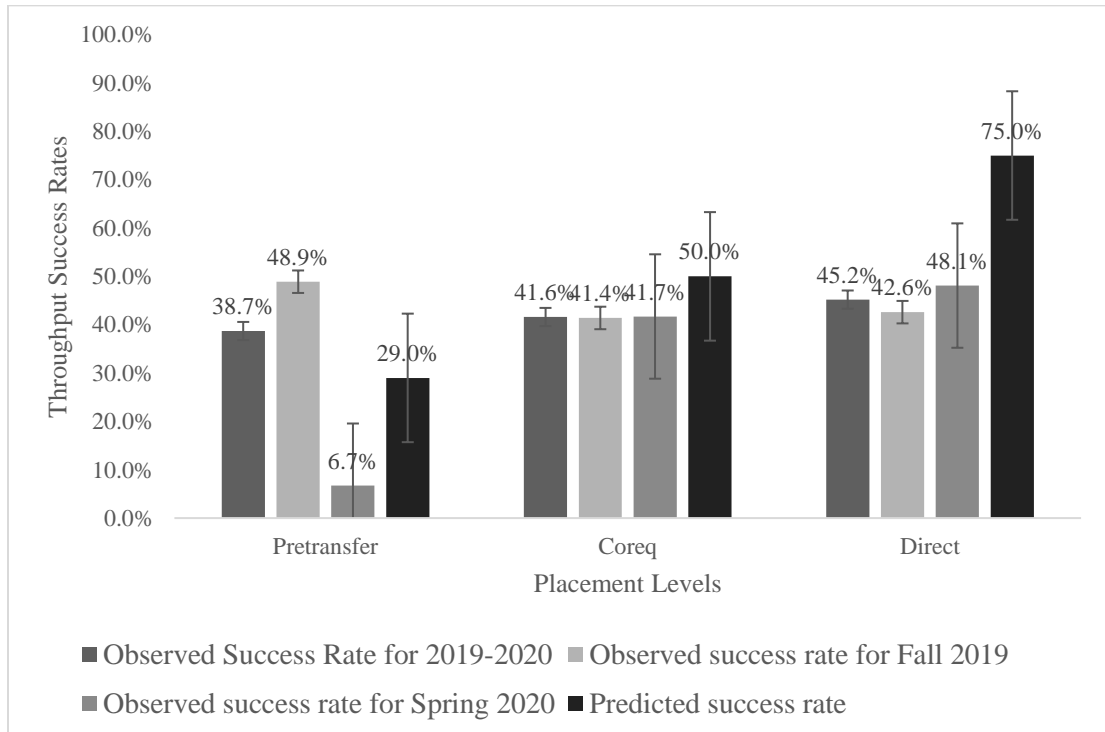


Figure 3

Throughput Success Rates for non-STEM Pathway



Tables 5, 6, and 7 display results from two-proportions z -test for placement level 1 (*Direct*), placement level 1 (*Coreq*), and placement level 1 (*Pretransfer*) respectively in the STEM pathway. The number of responses for STEM pathway in the predicted throughput was obtained from the Mathematics Placement Modes for the Multiple Measures Assessment Project – Phase II study (November 2016) related to the math decision trees which provided the rule sets for the default placement rules and the estimated success rates. The study used data from 31,386 STEM math students and 117,201 non-STEM math students from 103 colleges (MMAP Team, 2018).

Table 5

Two Proportions z -Test for the Difference between Observed and Predicted success rates for the Placement Level 1 (Direct) in STEM pathway

Samples	Responses	n	Proportion	SD	SE
Observed_Throughput	129	351	0.37	0.48	0.03
Predicted Throughput	23464	31286	0.75	0.43	0.00

Note. $z = -14.77$, $p < .001$, 95% CI: [-0.43, -0.33]

Table 6

Two Proportions z -Test for the Difference between Observed and Predicted success rates for the Placement Level 2 (Coreq) in STEM pathway

Samples	Responses	n	Proportion	SD	SE
Observed_Throughput_	82	169	0.48	0.50	0.04
Predicted Throughput	16582	31286	0.53	0.50	0.00

Note. $z = -1.17$, $p = .243$, 95% CI: [-0.12, 0.03]

Table 7

Two Proportions z -Test for the Difference between Observed and Predicted success rates for the Placement Level 3 (Pretransfer) in STEM pathway

Samples	Responses	n	Proportion	SD	SE
Observed_Throughput	3	4	0.75	0.43	0.22
Predicted Throughput	8760	31286	0.28	0.45	0.00

Note. $z = 2.17$, $p = .030$, 95% CI: [0.05, 0.89]

Tables 8, 9, and 10 display results from two-proportions z -test for placement level 1 (*Direct*), placement level 1 (*Coreq*), and placement level 1 (*Pretransfer*) respectively in the non-STEM pathway.

Table 8

Two Proportions z -Test for the Difference between Observed and Predicted success rates for the Placement Level 1 (Direct) in Non-STEM pathway

Samples	Responses	n	Proportion	SD	SE
Observed_Throughput	777	1718	0.45	0.50	0.01
Predicted Throughput	87901	117201	0.75	0.43	0.00

Note. $z = -24.68$, $p < .001$, 95% CI: [-0.32, -0.27]

Table 9

Two Proportions z -Test for the Difference between Observed and Predicted success rates for the Placement Level 2 (Coreq) in Non-STEM pathway

Samples	Responses	n	Proportion	SD	SE
Observed Throughput	276	664	0.42	0.49	0.02
Predicted Throughput	58600	117201	0.5	0.50	0.00

Note. $z = -4.38$, $p < .001$, 95% CI: [-0.12, -0.05]

Table 10

Two Proportions z -Test for the Difference between Observed and Predicted success rates for the Placement Level 3 (Pretransfer) in Non-STEM pathway

Samples	Responses	n	Proportion	SD	SE
Observed_Throughput	48	124	0.39	0.49	0.04
Predicted Throughput	33988	117201	0.29	0.45	0.00

Note. $z = 2.22$, $p = .027$, 95% CI: [0.01, 0.18]

Table 11 shows the Kruskal-Wallis test for throughput grades by each of the three placement levels for the academic year 2019-20. Table 12 is the post hoc test which is a follow-up test based on the results from Table 11.

Table 11*Kruskal-Wallis Rank Sum Test for Throughput Grades by Placement Level*

Level	Mean Rank	χ^2	df	p
Direct (Placement Level 1)	178.00	20.12	2	< .001
Coreq (Placement Level 2)	136.00			
Pretransfer (Placement Level 3)	137.50			

Table 12*Pairwise Comparisons for the Mean Ranks of Throughput Grades by Levels of Placement*

Comparison	Observed Difference	Critical Difference
Direct (Level 1)-Coreq (Level 2)	42.00	29.37
Direct (Level 1)-Pretransfer (Level 3)	40.50	29.37
Coreq (Level 2)-Pretransfer (Level 3)	1.50	29.37

Note. Observed Differences > Critical Differences indicate significance at the $p < 0.05$ level.

Table 13 shows the Kruskal-Wallis test for throughput grades by each of the three placement levels for the Fall 2019 term. Table 14 is the post hoc test which is a follow-up test based on the results from Table 13.

Table 13*Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level for Fall 2019*

Level	Mean Rank	χ^2	df	p
Direct	94.83	6.98	2	.030
Pretransfer	76.14			
Coreq	73.03			

Table 14*Pairwise Comparisons for the Mean Ranks of Throughput Grades for Fall 2019*

Comparison	Observed Difference	Critical Difference
Direct-Pretransfer	18.69	22.98
Direct-Coreq	21.81	24.05
Pretransfer-Coreq	3.12	19.71

Note. Observed Differences > Critical Differences indicate significance at the $p < 0.05$ level.

Table 15 shows the Kruskal-Wallis test for throughput grades by each of the three placement levels for the Spring 2020 term. Table 16 is the post hoc test which is a follow-up test based on the results from Table 15.

Table 15*Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level for Spring 2020*

Level	Mean Rank	χ^2	<i>df</i>	<i>p</i>
Direct	82.66	11.34	2	.003
Pretransfer	61.10			
Coreq	63.59			

Table 16*Pairwise Comparisons for the Mean Ranks of Throughput Grades for Spring 2020*

Comparison	Observed Difference	Critical Difference
Direct-Pretransfer	21.56	21.79
Direct-Coreq	19.07	18.99
Pretransfer-Coreq	2.49	23.27

Note. Observed Differences > Critical Differences indicate significance at the $p < 0.05$ level.

Table 17 shows the Kruskal-Wallis test for throughput grades by each of the three placement levels filtered by age category of those students who were 25 years of age or

below. Table 18 is the post hoc test which is a follow-up test based on the results from Table 17.

Table 17

*Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level
Filtered by Age: 25 years and below*

Level	Mean Rank	χ^2	df	p
Direct	144.05	15.91	2	< .001
Pretransfer	111.67			
Coreq	109.74			

Table 18

*Pairwise Comparisons for the Mean Ranks of Throughput Grades by Levels of Placement
Filtered by Age: 25 years and below*

Comparison	Observed Difference	Critical Difference
Direct-Pretransfer	32.38	27.44
Direct-Coreq	34.31	25.90
Pretransfer-Coreq	1.93	26.10

Note. Observed Differences > Critical Differences indicate significance at the $p < 0.05$ level.

Table 19 shows the Kruskal-Wallis test for throughput grades by each of the three placement levels filtered by gender category of female students. Table 20 is the post hoc test which is a follow-up test based on the results from Table 19.

Table 19

*Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level
Filtered by Gender: Female*

Level	Mean Rank	χ^2	df	p
Direct	103.54	14.25	2	< .001
Pretransfer	75.35			
Coreq	79.75			

Table 20

Pairwise Comparisons for the Mean Ranks of Throughput Grades by Levels of Placement Filtered by Gender: Female

Comparison	Observed Difference	Critical Difference
Direct-Pretransfer	28.19	22.02
Direct-Coreq	23.79	22.50
Pretransfer-Coreq	4.40	22.13

Note. Observed Differences > Critical Differences indicate significance at the $p < 0.05$ level.

Table 21 shows the Kruskal-Wallis test for throughput grades by each of the three placement levels filtered by ethnicity category of Hispanic/Latino students. Table 22 is the post hoc test which is a follow-up test based on the results from Table 21.

Table 21

Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level Filtered by Ethnicity: Hispanic/Latino

Level	Mean Rank	χ^2	<i>df</i>	<i>p</i>
Direct	129.90	23.05	2	< .001
Pretransfer	96.28			
Coreq	89.58			

Table 22

Pairwise Comparisons for the Mean Ranks of Throughput Grades by Levels of Placement Filtered by Ethnicity: Hispanic/Latino

Comparison	Observed Difference	Critical Difference
Direct-Pretransfer	33.62	24.65
Direct-Coreq	40.32	24.74
Pretransfer-Coreq	6.69	24.10

Note. Observed Differences > Critical Differences indicate significance at the $p < 0.05$ level.

Tables 23, 24, and 25 shows the Kruskal-Wallis test for throughput grades by each of the three placement levels filtered by DSPS, EOPS, and CalWORKs students, respectively.

Table 23

Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level

Filtered by DSPS Status: Yes

Level	Mean Rank	χ^2	<i>df</i>	<i>p</i>
Direct	13.00	5.85	2	.054
Pretransfer	9.00			
Coreq	6.50			

Table 24

Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level

Filtered by EOPS Status: Yes

Level	Mean Rank	χ^2	<i>df</i>	<i>p</i>
Direct	26.70	0.92	2	.633
Pretransfer	23.14			
Coreq	26.29			

Table 25

Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level

Filtered by CalWORKs Status: Yes

Level	Mean Rank	χ^2	<i>df</i>	<i>p</i>
Direct	1.50	1.78	2	.411
Pretransfer	3.17			
Coreq	4.00			

Table 26 shows the Kruskal-Wallis test for throughput grades by each of the three placement levels filtered by pathway choice category of non-STEM students. Table 27 is the post hoc test which is a follow-up test based on the results from Table 26.

Table 26

*Kruskal-Wallis Rank Sum Test for Throughput Grade by Placement Level
Filtered by Pathway: Non-STEM*

Level	Mean Rank	χ^2	df	p
Direct	130.89	19.01	2	< .001
Pretransfer	96.36			
Coreq	98.72			

Table 27

*Pairwise Comparisons for the Mean Ranks of Throughput Grades by Levels of Placement
Filtered by Pathway: Non-STEM*

Comparison	Observed Difference	Critical Difference
Direct-Pretransfer	34.53	23.03
Direct-Coreq	32.17	28.76
Pretransfer-Coreq	2.36	27.28

Note. Observed Differences > Critical Differences indicate significance at the $p < 0.05$ level

Table 28 displays the disaggregated data for the throughput success rates for the terms Fall 2019 and Spring 2020 filtered by those who successfully completed the transfer-level course/sequence by earning a grade C or better. The count and the percentages are presented for the throughput status, age, gender, ethnicity, DSPS, EOPS, and CalWORKs categories. The data count and corresponding percentages are calculated based on the placement levels that students were first placed at the time of enrollment.

Table 28

*Frequency Table for Nominal and Ordinal Variables based on throughput success rate
Filtered by Successfully Completed Category*

Variable	Fall 2019	Spring 2020
Placement Level		
Direct	11 (13%)	20 (31%)
Coreq	33 (39%)	26 (41%)
Pretransfer	40 (48%)	18 (28%)
Gender		
Female	46 (55%)	41 (64%)
Male	38 (45%)	23 (36%)
EOPS		
Yes	10 (12%)	13 (20%)
No	74 (88%)	51 (80%)
CalWORKs		
Yes	1 (1%)	1 (2%)
No	83 (99%)	63 (98%)
Ethnicity		
Hispanic/Latino	60 (71%)	42 (66%)
Not Hispanic / Not Latino	24 (29%)	22 (34%)
DSPS		
Yes	4 (5%)	3 (5%)
No	80 (95%)	61 (95%)
Age		
25 years and below	72 (86%)	48 (75%)
Above 25 years	12 (14%)	16 (25%)
Pathway		
Non-STEM	57 (68%)	44 (69%)
STEM	27 (32%)	20 (31%)

Note. Due to rounding errors, column wise percentages may not equal 100%.

Tables 29, 30, 31, 32, 33, 34, and 35 show the two proportions z -test for throughput success (successful completion) when compared between the Fall 2019 and Spring 2020 terms disaggregated by age (25 years and below), gender (female), ethnicity (Hispanic/Latino), DSPS, EOPS, CalWORKs, and pathway (non-STEM) respectively.

Table 29

Two Proportions z-Test for the Difference in Successful Completion between F19 and S20

Disaggregated by Age: 25 Years and Below

Samples	Responses	<i>n</i>	Proportion	<i>SD</i>	<i>SE</i>
Age: 25 Years and below F19	72	84	0.86	0.35	0.04
Age: 25 Years and below S20	48	64	0.75	0.43	0.05

Note. $z = 1.67$, $p = .096$, 95% CI: [-0.02, 0.24]

Table 30

Two Proportions z-Test for the Difference in Successful Completion between F19 and S20

Disaggregated by Gender: Female

Samples	Responses	<i>n</i>	Proportion	<i>SD</i>	<i>SE</i>
Gender: Female F19	46	84	0.55	0.50	0.05
Gender: Female S20	41	64	0.64	0.48	0.06

Note. $z = -1.11$, $p = .266$, 95% CI: [-0.25, 0.07]

Table 31

Two Proportions z-Test for the Difference in Successful Completion between F19 and S20

Disaggregated by Ethnicity: Hispanic/Latino

Samples	Responses	<i>n</i>	Proportion	<i>SD</i>	<i>SE</i>
Ethnicity: Hispanic/Latino F19	60	84	0.71	0.45	0.05
Ethnicity: Hispanic/Latino S20	42	64	0.66	0.47	0.06

Note. $z = 0.65$, $p = .517$, 95% CI: [-0.10, 0.20]

Table 32

Two Proportions z-Test for the Difference in Successful Completion between F19 and S20

Disaggregated by DSPS: Yes

Samples	Responses	<i>n</i>	Proportion	<i>SD</i>	<i>SE</i>
DSPS: Yes_F19	4	84	0.05	0.22	0.02
DSPS: Yes_S20	3	64	0.05	0.22	0.03

Note. $z = 0.00$, $p = 1.000$, 95% CI: [-0.07, 0.07]

Table 33

Two Proportions z-Test for the Difference in Successful Completion between F19 and S20

Disaggregated by EOPS: Yes

Samples	Responses	<i>n</i>	Proportion	<i>SD</i>	<i>SE</i>
EOPS: Yes_F19	10	84	0.12	0.32	0.04
EOPS: Yes S20	13	64	0.2	0.40	0.05

Note. $z = -1.31$, $p = .192$, 95% CI: [-0.20, 0.04]

Table 34

Two Proportions z-Test for the Difference in Successful Completion between F19 and S20

Disaggregated by CalWORKs: Yes

Samples	Responses	<i>n</i>	Proportion	<i>SD</i>	<i>SE</i>
CalWORKs: Yes_F19	1	84	0.01	0.10	0.01
CalWORKs: Yes S20	1	64	0.02	0.14	0.02

Note. $z = -0.49$, $p = .627$, 95% CI: [-0.05, 0.03]

Table 35

Two Proportions z-Test for the Difference in Successful Completion between F19 and S20

Disaggregated by Pathway: Non-STEM

Samples	Responses	<i>n</i>	Proportion	<i>SD</i>	<i>SE</i>
Pathway: Non-STEM F19	57	84	0.68	0.47	0.05
Pathway: Non-STEM S20	44	64	0.69	0.46	0.06

Note. $z = -0.13$, $p = .897$, 95% CI: [-0.16, 0.14]

Findings

In this section, I have presented the findings of the study based on the results section.

Findings on Research Question 1

Tables 1 through 10 pertain to results related to research question 1.

Descriptive Statistics

Tables 1, 2, 3, 4 and Figures 2, 3 provided descriptive statistics. Upon inspection, the throughput success rates from the local college did not meet or exceed the state's predicted success rates for both the STEM and non-STEM pathways when measured for the academic year 2019-2020 as well as when split by semester terms – Fall 2019 and Spring 2020. The Pretransfer level did exceed the State's success rates in most cases, but the initial cohort size was either very small or none as noted in one instance.

Two Proportions z-test for STEM

A two proportions z -test was conducted to examine whether there was a significant difference between the proportions of observed and predicted throughput success rates for STEM pathway by each level of placement, namely, the *Direct*, *Coreq*, and *Pretransfer*. The assumption of normality was assessed using the Central Limit Theorem (CLT). With a sufficiently large sample size ($n > 50$), deviations from normality will have little effect on the results (Pituch & Stevens, 2015). The sample size ($n_{s1} = 351$, $n_{s2} = 31286$) for *Direct*, the sample size ($n_{s1} = 169$, $n_{s2} = 31286$) for *Coreq*, and the sample size ($n_{s1} = 4$, $n_{s2} = 31286$) for *Pretransfer* were analyzed. The normality was violated in only one group, the Observed_throughput_Pretransfer_STEM due to low sample size.

Two Proportions z-test for Placement Level 1 (Direct) for STEM. In Table 5, the result of the two proportions z-test was significant based on an alpha value of 0.05, $z = -14.77$, $p < .001$, 95% CI = [-0.43, -0.33], indicating the null hypothesis can be rejected. For the *Direct* level in STEM category, this suggested that the proportion of observed throughput was significantly lower than the proportion of the predicted throughput. The 95% confidence interval for the difference between the proportions of Observed throughput Direct_STEM and Predicted_throughput_Direct_STEM was -0.43 to -0.33.

Two Proportions z-test for Placement Level 2 (Coreq) for STEM. In Table 6, the result of the two proportions z-test was not significant based on an alpha value of 0.05, $z = -1.17$, $p = .243$, 95% CI = [-0.12, 0.03], indicating the null hypothesis cannot be rejected. For the *Coreq* level in STEM category, this suggested there was no significant difference between the proportions of the observed and predicted throughput. The 95% confidence interval for the difference between the proportions of Observed throughput Coreq_STEM and Predicted_throughput_Coreq_STEM was -0.12 to 0.03.

Two Proportions z-test for Placement Level 3 (Pretransfer) for STEM. In Table 7, the result of the two proportions z-test was significant based on an alpha value of 0.05, $z = 2.17$, $p = .030$, 95% CI = [0.05, 0.89], indicating the null hypothesis can be rejected. For the *Pretransfer* level in STEM category, this suggested the proportion of the observed throughput was significantly higher than the proportion of the predicted throughput. However, it should be note with caution that this significance may be impacted by the normality violation (low sample size of observed *Pretransfer* level). The 95% confidence interval for the difference between the proportions of Observed

throughput Pretransfer_STEM and Predicted_throughput_Pretransfer STEM was 0.05 to 0.89.

Two Proportions z-test for Non-STEM

A two proportions z -test was conducted to examine whether there was a significant difference between the proportions of observed and predicted throughput success rates for Non-STEM pathway by each level of placement, namely, the *Direct*, *Coreq*, and *Pretransfer*. The assumption of normality was assessed using the Central Limit Theorem (CLT). With a sufficiently large sample size ($n > 50$), deviations from normality will have little effect on the results (Pituch & Stevens, 2015). The sample size ($n_{s1} = 1718$, $n_{s2} = 117201$) for *Direct*, the sample size ($n_{s1} = 664$, $n_{s2} = 117201$) for *Coreq*, and the sample size ($n_{s1} = 124$, $n_{s2} = 117201$) for *Pretransfer* were analyzed. The assumption of normality was not violated for any group.

Two Proportions z-test for Placement Level 1 (Direct) for Non-STEM.

In Table 8, the result of the two proportions z -test was significant based on an alpha value of 0.05, $z = -24.68$, $p < .001$, 95% CI = [-0.32, -0.27], indicating the null hypothesis can be rejected. For the *Direct* level in non-STEM category, this suggested that the proportion of observed throughput was significantly lower than the proportion of the predicted throughput. The 95% confidence interval for the difference between the proportions of Observed_throughput_Direct_Non_STEM and Predicted throughput_Direct_Non_STEM was -0.32 to -0.27.

Two Proportions z-test for Placement Level 2 (Coreq) for Non-STEM.

In Table 9, the result of the two proportions z -test was significant based on an alpha value of 0.05, $z = -4.38$, $p < .001$, 95% CI = [-0.12, -0.05], indicating the null hypothesis can be

rejected. For the *Coreq* level in non-STEM category, this suggested observed throughput was significantly lower than the proportion of the predicted throughput. The 95% confidence interval for the difference between the proportions of Observed throughput *Coreq_Non-STEM* and Predicted_throughput_*Coreq Non-STEM* was -0.12 to -0.05.

Two Proportions z-test for Placement Level 3 (Pretransfer) for Non-STEM.

In Table 10, the result of the two proportions *z*-test was significant based on an alpha value of 0.05, $z = 2.22$, $p = .027$, 95% CI = [0.01, 0.18], indicating the null hypothesis can be rejected. For the *Pretransfer* level in non-STEM category, this suggested that the proportion of the observed throughput was significantly higher than the proportion of the predicted throughput. The 95% confidence interval for the difference between the proportions of Observed throughput_*Pretransfer_Non-STEM* and Predicted throughput *Pretransfer_Non_STEM* was 0.01 to 0.18.

Findings on Research Question 2

Tables 11 through 27 pertain to results related to research question 1.

Kruskal-Wallis Rank Sum Test

A Kruskal-Wallis rank sum test was conducted to assess if there were significant differences in the throughput grade between the levels of placement. The Kruskal-Wallis test is a non-parametric alternative to the one-way ANOVA and does not share the ANOVA's distributional assumptions (Conover & Iman, 1981).

In table 11, the results of the Kruskal-Wallis test were significant based on an alpha value of 0.05, $\chi^2(2) = 20.12$, $p < .001$, indicating that the mean rank of throughput grade was significantly different between the levels of placement.

Post-hoc. Since the Kruskal-Wallis test showed significant difference, post hoc tests were performed as a follow-up to the main results as shown in table 12. Pairwise comparisons were examined between each level of placement. The results of the multiple comparisons indicated significant differences based on an alpha value of 0.05 between the following variable pairs: *Direct-Pretransfer* and *Direct-Coreq*.

Filtered by Fall 2019. When the results were filtered by Fall 2019 (Table 13), the results of the Kruskal-Wallis test were significant based on an alpha value of 0.05, $\chi^2(2) = 6.98$, $p = .030$, indicating that the mean rank of throughput grade was significantly different between the levels of placement. Pairwise comparisons were examined between each level of placement level. The results from table 14 indicated that none of the individual pairwise comparisons were significantly different.

Filtered by Spring 2020. When the results were filtered by Spring 2020 (Table 15), the results of the Kruskal-Wallis test were significant based on an alpha value of 0.05, $\chi^2(2) = 11.34$, $p = .003$, indicating that the mean rank of throughput grade was significantly different between the levels of placement level. Pairwise comparisons were examined between each level of the three placement level. The results of the multiple comparisons from table 16 indicated significant differences based on an alpha value of 0.05 between *Direct-Coreq*.

Kruskal-Wallis Test for Disaggregated Data

A Kruskal-Wallis rank sum test was conducted to assess if there were significant differences in throughput grade between the levels of placement when disaggregated by age, gender, ethnicity, DSPS, status, EOPS status, CalWorks status, and pathway choice.

Age. For Fall 2019, the most frequently observed category for Age was *25 years and below* ($n = 72, 86\%$). For Spring 2020, the most frequently observed category of Age was *25 years and below* ($n = 48, 75\%$). Hence, the test was run filtered by *25 years and below* from the Age category of student subpopulation. In table 17, the results of the Kruskal-Wallis test were significant based on an alpha value of 0.05, $\chi^2(2) = 15.91, p < .001$, indicating that the mean rank of throughput grade was significantly different between the levels of placement. In table 18, post hoc tests were followed. The results of the multiple comparisons indicated significant differences based on an alpha value of 0.05 between the following variable pairs: *Direct-Pretransfer* and *Direct-Coreq*.

Gender. For Fall 2019, the most frequently observed category of Gender was *Female* ($n = 46, 55\%$). For Spring 2020, the most frequently observed category of Gender was *Female* ($n = 41, 64\%$). Hence, the test was run filtered by *female* under gender category of student subpopulation. In table 19, the results of the Kruskal-Wallis test were significant based on an alpha value of 0.05, $\chi^2(2) = 14.25, p < .001$, indicating that the mean rank of throughput grade was significantly different between the levels of placement. In table 20, post hoc tests were followed. The results of the multiple comparisons indicated significant differences based on an alpha value of 0.05 between the following variable pairs: *Direct-Pretransfer* and *Direct-Coreq*.

Ethnicity. For Fall 2019, the most frequently observed category of Ethnicity was *Hispanic/Latino* ($n = 60, 71\%$). For Spring 2020, the most frequently observed category of Ethnicity was *Hispanic/Latino* ($n = 42, 66\%$). Hence, the test was run filtered by *Hispanic/Latino* under ethnicity category of student subpopulation. In table 21, the results of the Kruskal-Wallis test were significant based on an alpha value of 0.05, $\chi^2(2) = 23.05,$

$p < .001$, indicating that the mean rank of throughput grade was significantly different between the levels of placement level. In table 22, pairwise comparisons were examined between each level of placement level. The results of the multiple comparisons indicated significant differences based on an alpha value of 0.05 between the following variable pairs: *Direct-Pretransfer* and *Direct-Coreq*.

DSPS. Given the interest in knowing how this category of students fared, the test was run filtered by *Yes* under DSPS category of student subpopulation. In table 23, the results of the Kruskal-Wallis test were not significant based on an alpha value of 0.05, $\chi^2(2) = 5.85, p = .054$, indicating that the mean rank of throughput grade was similar for each level of placement level.

EOPS. Given the interest in knowing how this category of students fared, the test was run filtered by *Yes* under EOPS category of student subpopulation. In table 24, the results of the Kruskal-Wallis test were not significant based on an alpha value of 0.05, $\chi^2(2) = 0.92, p = .633$, indicating that the mean rank of throughput grade was similar for each level of placement level.

CalWORKs. Given the interest in knowing how this category of students fared, the test was run filtered by *Yes* under CalWORKs category of student subpopulation. In table 25, the results of the Kruskal-Wallis test were not significant based on an alpha value of 0.05, $\chi^2(2) = 1.78, p = .411$, indicating that the mean rank of throughput grade was similar for each level of placement level.

Pathway. For Fall 2019, the most frequently observed category of Pathway choice was *Non-STEM* ($n = 57, 68\%$). For Spring 2020, the most frequently observed category of Pathway choice was *Non-STEM* ($n = 44, 69\%$). Hence, the test was run

filtered by *Non-STEM* under pathway category of student subpopulation. In table 26, the results of the Kruskal-Wallis test were significant based on an alpha value of 0.05, $\chi^2(2) = 19.01$, $p < .001$, indicating that the mean rank of throughput grade was significantly different between the levels of placement level. In table 27, pairwise comparisons were examined between each level of placement level. The results of the multiple comparisons indicated significant differences based on an alpha value of 0.05 between the following variable pairs: *Direct-Pretransfer* and *Direct-Coreq*.

Findings on Research Question 3

Tables 28 through 35 pertain to results related to research question 1.

Descriptive Statistics

In table 28, the frequencies and percentages were calculated for placement level, gender, EOPS, CalWORKs, Ethnicity, DSPS, Age, and Pathway split by Fall 2019 and Spring 2020 terms.

Two-Proportion z-test for Disaggregated Data

A two proportions z-test was conducted to examine whether there was a significant difference between the proportions of throughput success when disaggregated by age, gender, ethnicity, DSPS, status, EOPS status, CalWorks status, and pathway choice. The assumption of normality was assessed using the Central Limit Theorem (CLT). All groups met the normality assumption requirement as they all had the sample size ($n_{s1} = 84$, $n_{s2} = 64$).

Age. In table 29, the result of the two proportions z-test was not significant based on an alpha value of 0.05, $z = 1.67$, $p = .096$, 95% CI = [-0.02, 0.24], indicating the null hypothesis cannot be rejected. This suggested there was no significant difference between

the proportions of F19 and S20 among those who were 25 years and below. The 95% confidence interval for the difference between the proportions of Age_25_Years_and_below_F19 and Age_25_Years_and_below_S20 was -0.02 to 0.24.

Gender. In table 30, the result of the two proportions z -test was not significant based on an alpha value of 0.05, $z = -1.11$, $p = .266$, 95% CI = [-0.25, 0.07], indicating the null hypothesis cannot be rejected. This suggested there was no significant difference between the proportions of F19 and S20 among those who were female. The 95% confidence interval for the difference between the proportions of Gender_Female_F19 and Gender_Female_S20 was -0.25 to 0.07.

Ethnicity. In table 31, the result of the two proportions z -test was not significant based on an alpha value of 0.05, $z = 0.65$, $p = .517$, 95% CI = [-0.10, 0.20], indicating the null hypothesis cannot be rejected. This suggested there was no significant difference between the proportions of F19 and S20 among those who were Hispanic/Latino. The 95% confidence interval for the difference between the proportions of Ethnicity_Hispanic_Latino_F19 and Ethnicity_Hispanic_Latino_S20 was -0.10 to 0.20.

DSPS. In table 32, the result of the two proportions z -test was not significant based on an alpha value of 0.05, $z = 0.00$, $p = 1.000$, 95% CI = [-0.07, 0.07], indicating the null hypothesis cannot be rejected. This suggested there was no significant difference between the proportions of F19 and S20 among those of DSPS status. The 95% confidence interval for the difference between the proportions of DSPS_F19 and DSPS_S20 was -0.07 to 0.07.

EOPS. In table 33, the result of the two proportions z -test was not significant based on an alpha value of 0.05, $z = -1.31$, $p = .192$, 95% CI = [-0.20, 0.04], indicating

the null hypothesis cannot be rejected. This suggested there was no significant difference between the proportions of F19 and S20 among those of EOPS status. The 95% confidence interval for the difference between the proportions of EOPS_F19 and EOPS_S20 was -0.20 to 0.04.

CalWORKs. In table 34, the result of the two proportions z -test was not significant based on an alpha value of 0.05, $z = -0.49$, $p = .627$, 95% CI = [-0.05, 0.03], indicating the null hypothesis cannot be rejected. This suggested there was no significant difference between the proportions of F19 and S20 among those of CalWORKs status. The 95% confidence interval for the difference between the proportions of CalWORKs_F19 and CalWORKs_S20 was -0.05 to 0.03.

Pathway. In table 35, the result of the two proportions z -test was not significant based on an alpha value of 0.05, $z = -0.13$, $p = .897$, 95% CI = [-0.16, 0.14], indicating the null hypothesis cannot be rejected. This suggested there was no significant difference between the proportions of proportions of F19 and S20 among those who were in Non-STEM pathway. The 95% confidence interval for the difference between the proportions of Pathway_Non_STEM_F19 and Pathway_Non_STEM_S20 was -0.16 to 0.14.

Discussion

In this section, I have presented the discussions on the study based on the findings section.

Discussion on Research Question 1

The research questions focused on comparing the local observed throughput success rate with the State's predicted success rates as provided in Appendices C and D for non-STEM and STEM pathways, respectively. Basic comparison of the success rates

indicated that the observed success rates failed to meet the predicted success rates at every placement level in both pathways. The findings showed that there is not a statistically significant difference between the observed throughput success rates and the predicted success rates for STEM pathway for the *Coreq* placement level. There was a statistical difference in the *Direct* level and *Pretransfer* level but the latter must be interpreted with caution due to low cohort size. The findings showed that there was a statistically significant difference between the observed throughput success rates and the predicted success rates for the non-STEM pathway. It was statistically significantly lower for the *Direct* placement level and the *Coreq* placement level while it showed statistically significantly higher for the *Pretransfer* level.

Discussion on Research Question 2

The focus of this research question was to determine if the placement levels had any effect on throughput grades. The findings for the academic year 2019-2020 showed that there was a statistically significant difference in the throughput grades by the three levels of placement. Post hoc pairwise comparisons further revealed statistically significant differences between *Direct-Pretransfer* and *Direct-Coreq* levels. When the data was filtered by terms to determine the singular effects, the Fall 2019 findings showed there was a statistically significant difference in the throughput grades by the three levels of placement, but the pairwise comparison did not show statistical significance. However, Spring 2020 findings showed that there was a statistically significant difference in the throughput grades between the *Direct-Coreq* levels.

Findings from disaggregated data showed the following:

- Age (25 years and below), Gender (Female), Ethnicity (Hispanic/Latino), and Pathway (Non-STEM) categories showed statistically significant difference in the throughput grade, particularly between *Direct-Pretransfer* and *Direct-Coreq* levels.
- DSPS, EOPS, and CalWORKs categories showed no showed statistically significant difference in the throughput grade, indicating that the throughput grades were similar for each placement level.

Discussion on Research Question 3

The focus in this research question was to determine any difference in the proportions of throughput success rates in Fall 2019 versus Spring 2020 for each student category, irrespective of their placement level. The descriptive statistics gave an overview of the throughput success rates of all the categories split by terms. The findings revealed that there was not a statistically significant difference in the proportions of throughput success rates for Fall 2019 and Spring 2020 by any of the student categories, disaggregated by age, gender, ethnicity, DSPS, status, EOPS status, CalWorks status, and pathway choice.

Summary

The data analysis and statistical interpretation revealed many pertinent details related to throughput student success in transfer-level mathematics students. The AB705 law requires that all students be placed in transfer-level courses either with or without support, unless colleges can show that those students would be highly unlikely to succeed (Hope & Stankas, 2018). Numerical comparison of the success rates indicated that the local observed success rates failed to meet the state's projected success rate. Statistical

comparison of the observed with the predicated success rates showed there was a statistically significant difference in their throughput. The observed success rates were significantly lower than the predicted success rates. However, the *Coreq* placement showed some promise as it deviated the least from the desired success rate.

There was a statistically significant difference in the throughput between the placement levels, particularly between the *Direct-Pretransfer* and *Direct-Coreq* levels. The findings revealed that the success rate was statistically significantly lower in the transfer-level placements with or without support, namely Placement Level 1 (*Direct*) and Placement Level 2 (*Coreq*) when compared to the Placement Level 3 (*Pretransfer*). Although the throughput success rates were statistically significantly higher for Placement Level 3 (*Pretransfer*), it is not practically significant given that the cohort size was very small. This was true for both the STEM and non-STEM pathway for both the terms, Fall 2019 and Spring 2020. Since the corequisite course was implemented only in Fall 2019, the redesigned curriculum could be further improvised in instruction, just-in-time remediation, and/or academic support services such as tutoring.

As for disaggregated data by demographics and special services, the numbers seemed consistent with the student subpopulation. Among those who successfully completed their transfer-level courses, the following were observed: Age (25 and below), Gender (Female), Ethnicity (Hispanic/Latino), and Pathway (Non-STEM) outperformed their counterparts in both the terms. When the proportions of success rates were compared between semesters (Fall 2019 and Spring 2020) among the student categories, it was found that there was no statistically significant difference for any student category

under study. However, an exclusive study on disproportionate impact must be conducted as a follow-up to this study to determine any significant presence of equity gaps.

CHAPTER FIVE: PROPOSED SOLUTION AND IMPLICATIONS

In this chapter, I have addressed the study's aim and proposed recommendations that suggest solutions, described procedures for implementation, and discussed practical, research-related, and leadership-related implications. The chapter closed with a final summary and conclusion of this Dissertation in Practice study.

Aim Statement

The AB 705 California law has mandated placement reforms that colleges must no longer use the placement tests but instead incorporate multiple measures of assessment policy for student placement that uses high school achievement data, including the HSGPA (Belfield & Crosta, 2012). This change is expected to place most students directly in transfer-level courses, thus eliminating the traditional, remedial sequence of courses. Also, students will get to choose their desired pathways, such as STEM or non-STEM, at the time of enrollment so that the guided pathways will help them complete their sequence of required courses for transfer in a timely manner. The purpose of this study is to validate the effectiveness of the placement reforms in central California community colleges to determine if the changes truly maximized the throughput success rates (AB705 Student Success Act, 2017).

Proposed Solutions

As noted in the dissertation, Spring 2020 was a challenging semester given the COVID-19 pandemic which caused all face-to-face classes to be transitioned into fully online courses. It was also the time when many students who were parents had to care for their children, the elderly, or other dependents in their household. The fear of exposure, lack of resources such as laptops and internet accessibility, loss of jobs, and changes in

lifestyle and routine prompted many students to push education to the back seat. Based on the results, findings, and discussions in Chapter 4, the solutions proposed here will be viewed both under normal circumstances and under emergency situations.

Evidence that Support the Solution

Pretransfer

The findings from Chapter 4 revealed that students who began at the *Pretransfer* level showed strong success rates in Fall 2019 while Spring 2020 findings showed completely the opposite. In Fall 2019, the pre-pandemic period, the cohort sizes were really small, making it hard to perform robust statistical tests to test for statistical significance, whereas in Spring 2020, the cohort sizes were negligent or non-existent. It must be acknowledged, though, that it statistical significance need not imply practical significance given that the throughput cohort sizes were small. Only a very few transfer-level students would benefit from being placed one level below transfer.

The Associate degree requires completion of the degree-applicable pretransfer level courses such as Math 61 (Algebra for STEM) and Math 62 (Algebra for non-STEM). For these reasons, it is wise to continue offering the Pretransfer-level courses with large enrollment. Nevertheless, the mathematics department must reassess their course offerings, the redesigned curriculum, and the transfer-intent of the students and then make a recommendation to the counseling department on the placement protocol of transfer students. Additionally, to prevent student attrition, the throughput cohort must be linked to the corresponding transfer-level course (if possible, automatically enrolled for the following term) so that students are aware of their ultimate destination.

Coreq

This placement level showed the most promise. The throughput success rates showed the least deviation among the placement levels from the predicted success rate and remained consistent in pre-pandemic period and the impacted period. When the corequisite support was introduced in the participating college, students were co-mingled with those who did not need support. In other words, for transfer-level course, the students from placement level 1 were mixed with those from placement level 2 and were taught by the same instructor at the same meeting days. Those who belonged to placement level 2 met with the same instructor at another time for the corequisite support. This was true with both the STEM and non-STEM pathways. This brought a host of problems both logistically as well as instructionally and could have influenced the results adversely as the confounding variable. So, the proposed solution is to offer the courses independently as cohorts instead of the co-mingled model. This will ensure equal class size so that the entire group receives equitable instructions in their respective classes without introducing maturation threat or internal validity issues. Logistically, the support course is a lab course and the cohort model instead of the comingled model will be more efficient with student interaction, lesson planning, course setup, course requirements, common syllabi, grading, and scheduling, to name a few.

Direct

This placement level showed the least throughput success rates and the most deviation from the baseline metrics. From a curriculum perspective, this course has been offered for many years and there were no curricular changes made to the course. Students with high GPA and with past prerequisite course completions are the ones who are

typically placed into Placement level 1. While the throughput rates are better than the pre-AB705 impact, the failure to meet the baseline metrics by nearly 40 percentage points indicates the course may require overhaul using backwards design.

I discovered that the mathematics department had put through Math 11 (Elementary Statistics – 4 credits), a revised transfer-level Statistics course and has been approved by the Chancellor’s Office. My proposed solution for the non-STEM pathway is for the faculty to offer Math 11 courses as soon as possible to replace the current transfer-level course, Math 10 (Elementary Statistics – 3 credits). The rationale offered by the faculty in their submission for the new 4-unit course explained the difficulties in covering the topics and just-in-time remediation for lack of time. These anecdotal experiences could very well be the core reason for the low success rates.

As for STEM pathway, possessing strong prerequisite skills of Algebra and Trigonometry is inarguably a key requirement for students to be able to handle the advanced Calculus concepts that the PreCalculus course is tasked with priming. However, students typically have trouble recalling Trigonometry concepts from past terms despite having performed well in those courses. The mathematics department in the participating college had put through Math 27 (Preparatory Calculus with Trigonometry – 6 credits), a revised transfer-level Precalculus course and has been approved by the Chancellor’s Office. By replacing the current Precalculus course (Math 2 – 4 credits) with Math 27 (6 credits), the low achievement scores could be reversed as this new course incorporates Trigonometry for better retentivity and remediation for students. Additionally, the new Math 27 course will help ease up and redirect resources (staffing,

scheduling, infrastructure) who would otherwise be occupied with teaching separate Math 25 (Trigonometry – 3 credits) and Math 2 courses creating more exit points.

Evidence that Challenges the Solution

Pretransfer

While I propose the solution to keep the Pretransfer level courses despite the mixed results and low throughput cohort, there are a few items to follow through when monitoring the throughput cohort. The AB705 advocates argued that remedial courses resulted in high attrition because of the lengthy developmental sequence for mathematics courses. That is, students placed in the remedial sequence are more likely to drop out when moving from one course to the next (known as exit points). Even one exit point presents a danger to the throughput cohort who start at the Pretransfer level because there is room for attrition when moving from the pretransfer to the transfer-level course.

Coreq

With the changes proposed, the mathematics department as well as the local AB705 task force must continue with the assessment and evaluation of throughput results in the cohort model to determine if there were any other confounding factors that could adversely impact the ability of the students as well as the instructors in participating and performing their best.

Direct

It is evident that the current Math 10 course which has been offered for several years has not met the baseline standards. When the math faculty decide to switch from Math 10 to Math 11, they will need to adapt to the teaching philosophy of backwards-design when planning their lessons as this would allow students to recover and reallocate

the time to incorporate just-in-time remediation without sacrificing the learning outcomes. If the department does not choose to switch to the 4-credit course offering of the transfer-level course, then they have to determine further evidence as to why the direct level failed to give the expected results. For STEM pathway, the heavy credits that Math 27 carries may be difficult for faculty to teach for long hours as well as for the students to carve out 6 hours per week for in-class instructions. At times of emergency, students might find it overwhelming to keep up with the rigor of the course when taught remotely because the regulations of the school demand that attendance cannot be made mandatory for live video lectures. Additionally, to create a corresponding corequisite course for an already high credit course may be both challenging and impractical for students and instructors alike.

Implementation of the Proposed Solution(s)

Linked or paired courses are popular as they provide a definitive destination that is attainable within a one-year timeframe as laid out in the AB705 law. If all throughput cohorts can be linked to their culminating transfer-level courses, be it Statistics in the non-STEM pathway or Precalculus in the STEM pathway, there is a high chance of improving the throughput success rate. When courses are linked, and preferably with the same instructor, there is a bond that is formed between the instructor and the students as they follow from one course to another. The familiarity of the instructional style, the instructor, and peers in a linked, cohort setup inculcates a sense of strong academic, emotional, and psychosocial support. This is particularly helpful in intensive courses.

As for students placed in placement level 3 - *Pretransfer*, I propose to create 6-week or 9-week courses (a similar format as the summer terms) and link them to another

6-week or 9-week transfer-level course. These courses should be ideally taught by the same instructor for continuity and effectiveness. If funding permits, embedded tutors can be added resource for students to reach out for remediation help. It is very important to maintain a small class size (no more than 35 students in the cohort) for effective use of time, attention, and resources to the students in a fast-paced environment. This kind of linked, short-term, accelerated approach may improve throughput success rates in the following ways: maintain strong cohort, increased student-teacher interaction for academic support, familiarity with the course set-up and expectations, just-in-time remediation, team-based learning, as well as camaraderie and lifelong friendships. By attending to the affective domain needs as well as cognitive load needs, a balanced environment is created that is conducive for learning.

An in-class experience of such accelerated courses may show a better success rate than unplanned, emergency remote learning wherein students are unable to choose from other learning options. Although the world is currently going through a pandemic and remote education has been the sole way of learning, emergencies will eventually pass, and when normalcy returns, the above-mentioned changes would be welcomed, and even popular, as many students seem to have put their education on hold for the crisis to pass. They would be very interested in finishing their courses and meeting their educational goals as soon as possible.

The linked, short-term, accelerated approach may work well for some courses in the non-STEM pathway (as they typically have lower credit courses) and may not be as suitable for some courses in the STEM pathway. Nevertheless, the courses could remain linked even if resorting to 18-week terms. If and whenever possible, the same instructor

may be encouraged to teach the same cohort the following term so that students are familiar with the instructional style and general course expectations.

Factors and Stakeholders Related to the Implementation of the Solution

The dean, the faculty, the instructional staff, advisors, counselors, financial aid, and other student academic and support services may be involved directly or indirectly and may be impacted in one way or another. The Office of Institutional Effectiveness will play a major role in continued assessment and data-driven decision-making. At the core, faculty buy-in and student adjustment are the key components in making the implementation a success. In an online learning environment, as in the pandemic response times, it is easier to be able to set up courses before the terms begin.

The Distance Education committee has put together several resources for self-help, mentoring, as well as training programs for faculty and students to help with the transition and creation of online courses. While it involves heavy preparation beforehand, it certainly becomes manageable and well-organized once the instruction formally begins. In a face-to-face traditional offering, the experience of meeting every day and having a personal interaction would help build presence and team spirit that is very much needed in a cohort system. However, it can cause severe fatigue when it involves teaching large credit courses for long contact hours. Co-teaching is another option that faculty can explore to share the unit load and reduce exhaustion. Wherever possible, pairing with a part-time faculty would also be beneficial in creating employment opportunities for them as well as fostering professional mentoring between the fulltime and part-time faculty.

The counselors and faculty need to work closely to ensure that students are correctly aligned by their pathways, correctly placed at the appropriate placement level,

and transfer-intent is correctly recorded showing history of changed plans (if any). HSGPA scores for entering students can be requested between institutions to avoid student self-reporting which may underplace students inadvertently. Based on the study findings, placing most students in the corequisite courses seemed to show the most potential. With the suggested changes to reduce to smaller cohort size, the throughput could be maximized. Also, switching to the newly approved courses could help improve the throughput for students in *Direct* transfer-level placement. The math department needs to devote its attention and resources to greatly maximize throughput for Placement level 1. Logistical and scheduling revisions will also need to be made to cater to the students' local needs, demands, and interests.

Timeline for Implementation of the Solution

A time allotment must be provided for every proposed solution. This will allow a devoted period to discuss, plan, prioritize, improve, seek approval, and then implement these solutions. An exception to this proposed time allotment might be the newly approved courses, Math 11 and Math 27 for *Direct* level as well as the linked, 9-week, accelerated courses for the *Pretransfer* level. These changes can be piloted/implemented as early as Spring 2021 as they are the levels that showed weakest throughputs. This timeline should not be impacted even if the college experiences practical limitations due to a post-COVID return or continues remote instruction offerings. It is hoped that the evidence from this dissertation in practice may be compelling enough to expedite the process. It is imperative to implement these proposed solutions in Spring 2021 to eliminate the logistic dissonance and thereby improve instantly the teaching and learning experience, which includes the throughputs. Even though Math 11 and Math 27 can be

piloted in Spring 2021 for one section and some more in Summer 2021, practical difficulties indicate that the schedules and enrollment which will begin shortly may preclude the replacement of the courses.

Evaluating the Outcome of Implementing the Solution

The local Office of Institutional Effectiveness (OIE), the local AB705 task force, and the mathematics department will have to work in tandem to assess for continuous improvement and innovation. The OIE will play a critical role in extracting the data requested by the task force and math department in a quick and efficient manner. The OIE will have to revamp its access to database and data mining, so that they are equipped to access all student information housed in different databases, be able to collate and manage them efficiently, and support staff and faculty with their research and inquiry. The updates could be provided after each census (there are three in a semester) for ongoing assessment of student retention within a semester. At the start of each semester, the throughput success rates for each placement level can be provided to the mathematics department for evaluation of their curricular changes.

Implications

Practical Implications

As far as AB 705 is concerned, the institution's local throughput failed to meet the State's threshold standards for the top two placement levels, *Direct* and *Coreq*. As per the memo guidelines, colleges that failed to meet the criterion must adopt the State's default placement rule as shown in Appendices C and D. However, interestingly, the participating college *did* adopt the default placement rule for the *Direct* and *Coreq* placement levels and deviated only for the *Pretransfer* placement level. Therefore,

assuming that the students were placed correctly in the transfer-level courses (at least, as per the AB 705 rights), the next level of investigation must be to study and determine whether 1) the majority of the students were academically unprepared/underprepared despite the higher HSGPA and other multiple measures, 2) the students were highly unlikely to succeed because of this placement, 3) the student engagement factors were not fully addressed, or 4) there was a failure in the curricular redesign, delivery, and/or implementation.

It is important to note that, when interpreting results, it is crucial to consider the count versus the percentage to get a wholesome picture of successful completion. A closer examination of the cohort numbers indicates that the majority of the students who took the pretransfer course did not return the consecutive semester to complete their transfer-level course.

There are three pretransfer courses, namely, Math 61 (Algebra for STEM), Math 62 (Algebra for non-STEM), and Math 88 (Pre-Statistics). Of the three, Math 88 is the only course that is not degree-applicable and therefore is of particular concern that not all those students went on to complete their transfer-level Elementary Statistics course. Appendices H and I provide snapshots of the throughput status (pass, fail, drop) by placement levels and by terms for each pathway.

Implications for Future Research

As for practical implications, further investigation needs to be conducted to understand why students would not take advantage of the elimination of remedial sequence even when placed directly in transfer-level courses. Further local research must be encouraged and supported through grants, stipends, release time, or banking hours.

Some immediate topics for study to maximize throughput are disproportionate impact in student subpopulations and effectiveness of remote instruction versus traditional instruction, short-term courses versus regular-term courses, and linked courses versus unlinked courses. If funding and resources permit, randomized experiments can be conducted to measure and study the effectiveness of complex qualitative variables on throughput success such as college readiness of students, targeted preparation, personal disposition, instructional methodology, and instructor likeability.

Other suggestions to conduct follow up research under comparable conditions to “scan the field” and make accountable recommendations are:

- Comparative analysis on throughput rates between remote modalities (virtual, hybrid, correspondence, fully online) versus in-person courses to validate effectiveness of remote course offerings and producing an impact report.
- Comparative analysis between classrooms with high and low success rates to study differences in implementation, and possible intervention.
- Local phenomenological studies on student learning and engagement in high-credit, accelerated formats to complement quantitative research on success rates.
- Local phenomenological studies on faculty engagement and pedagogical approach in co-mingled versus cohort models, particularly for corequisite courses and linked courses.
- Local faculty and counselor interviews using established protocols to reveal “inconvenient truths” that may have been ignored in the pilot development.

- Exclusive, larger study on disproportionate impact on student subpopulations and presence of any equity gaps.
- Investigate failed-to-succeed patterns through exit interview protocol, counselor records, and interventions to identify concentration areas for improvement.
- Create and mandate orientation/readiness workshop courses for first-time college students to orient them to college education, learning management system, online etiquette, and course expectations, to name a few.

Implications for Leadership Theory and Practice

Kuh's student success framework touched upon a myriad of internal and external factors that affect a student's success in postsecondary education. While external factors such as state and federal policies, globalism, economic forces, demographics, and accountability impacted students' college experience, it can be seen that these factors are not under their control. In his "What matters to student success" schematic in Figure 1, Kuh goes on to show that students' pre-collegiate experiences play an important role in college success. Once in college, a student's engagement is the single key determining factor that leads to desired post college outcomes such as graduation, employment, graduate or professional school, and other lifelong learning gains.

For the purpose of this study, I would like to focus on successful college experience by becoming mindful of the student engagement, especially students' learning experiences in the classroom. Kuh listed student behaviors such as study habits, peer involvement, interaction with faculty, time on task, and motivation that all play a role in these classroom learning experiences (Kuh et al., 2006). Kuh went on to describe

institutional conditions such as first year experiences, academic support, campus environment, time on task, peer support, teaching and learning approaches as other major forces that act internally within the college that influences student success. My research focused on a quantitative look at whether the placement level of a student when first entering the college has an effect on the throughput success. This indirectly involves the influence of redesigned curriculum, academic support, teaching and learning approaches, and student engagement, as discussed by Kuh, on student success.

Most educational reforms have the best intention in conception, but transferability and scalability of the ideas and importantly, the implementation of them can distort the expected results. To that end, the emphasis on student success cannot and must not be limited to quantitative information. Rather, the data results must be used to validate the learning experiences that takes place within the classroom/course and the institutional conditions that also impact student learning for a complete, balanced picture. The Chancellor's Office must highlight the importance of collecting evidence from both qualitative and quantitative measures of factors that impact learning, not just completion.

The phenomenological aspects of learning in college as well as instructional style and habits need to be studied in order to understand the motive to quit or remain inactive. One aspect that has not been fully explored is the opinions and difficulty of the instructor in gauging and improving student mastery. AB705 task force in local colleges need to bring faculty into the conversation through faculty forums. Their perspective should be considered as leadership initiatives are developed to improve the overall college experience and bring about rigor in educational benchmarks. These initiatives could help normalize high standards of education. As well, the students' positive mindset and voice

when heard also foster their academic lifetime successes as part of post-collegiate outcomes. Hence, students must be required to attend education symposiums as part of their college curriculum where the purpose is to create awareness about education, instead of a singular focus on throughput scores which aims at completion rather than cognition.

Furthermore, recent events have highlighted the need for flexibility. Ongoing and future emergencies like pandemics, epidemics, wildfires, poor air quality, and other natural calamities, have caused a shift in paradigms for learning modalities in higher education. Therefore, remote learning is germane to the future of education and needs to be considered with utmost importance. Preparedness for such times calls for the necessity to strengthen online teaching/learning initiatives through in-house workshops, on-demand teaching and technology trainings, certifications, peer-reviews, and academy badges (digital recognition and display of online credentials for quality courses). Symposiums and professional development for students, faculty, and staff, are imperative for transition into higher education. Additionally, initiatives that focus on educational technology, literacy advocacy, and mandatory orientation courses on college readiness, guided pathways, online readiness, college expectations and outcomes, and education on education (what I would like to call *meta-educere*) could all facilitate student success.

Summary of the Dissertation in Practice

I started on a quest as a researcher to understand interdisciplinary leadership in the field of education by studying the recent educational reforms introduced by the AB705 legislation in California. The AB 705 law required all 115 California community colleges to implement and come into full compliance by Fall 2019. All California

community college districts were required to “maximize the probability that a student will enter and complete transfer-level coursework in Math and English within a one-year timeframe by utilizing assessment measures that include high school performance to achieve this goal” (AB705, 2017, para 1). The law was supplemented by a memo, released by the Chancellor’s Office in July 2018, in collaboration with the Academic Senate of California community colleges that provided the rationale, the “default placement rules” for each pathway, and the corresponding predicted success rates for each placement level (Hope & Stankas, 2018). The AB 705 memo made clear that colleges that deviated from the default placement rules (to suit their local needs) were allowed to do so, provided they validated their local placement changes and decisions that showed that their innovation met or exceeded the State’s projected success rates. The default rules can be found in Appendices C and D. The participating college in this study revised its placement rules in accordance with the law. However, they replaced the lowest placement level for students with low HSGPA and missing prerequisites to be instead placed one-level-below transfer level known as the Pretransfer-level. The revised placement rules can be found in Appendices A and B.

The purpose and aim of this study were to validate the revised placement rules and how it maximized the throughput success of transfer-level mathematics students. Using a causal-comparative retrospective throughput analysis, I was able to determine that there was a statistically significant difference in the throughput between the observed success rates and the State’s projected success rates for the Non-STEM pathway but only in the *Pretransfer* level in the STEM pathway. Numerical comparison of the throughput rates showed that the throughput success rates of the participating college failed to meet

the state's projected success rates. As for the effect of the placement level on the throughput success rates in the non-STEM pathway, the findings revealed that the success rate was significantly lower in the transfer-level placements with or without support, namely Placement Level 1 (*Direct*) and Placement Level 2 (*Coreq*) while the throughput success rates were statistically significantly higher for Placement Level 3 (*Pretransfer*). However, it is not practically significant given that the *Pretransfer* cohort size was very small. It must also be noted that the COVID-19 lockdown might have introduced many confounding factors into the data of Spring 2020 due to changes in instructional delivery method as well as the lifestyle and livelihood changes caused by the pandemic.

As for disaggregated data by demographics and special services, the numbers seemed consistent with the student subpopulation. Among those who successfully completed their transfer-level courses, the following were observed: Age (25 and below), Gender (Female), Ethnicity (Hispanic/Latino), and Pathway (Non-STEM) outperformed their counterparts in both the terms. When the proportions of success rates were compared between semesters (Fall 2019 and Spring 2020), it was found that there was no statistically significant difference for any student category under study. However, a disproportionate impact study must be conducted as a follow-up to determine any significant presence of equity gaps.

The low throughput success rates, particularly in the Direct placement level indirectly revealed that the students were not taking advantage of the fact that they did not have to endure several years of remedial math courses and that they could be “in and out” of college within one semester, if not one year. Previous studies indicated socio-

economic disparity and dependent care as concerning reasons and blocks for student access and success. However, it must be noted that California educational system has one of the largest student aid support services and a plethora of scholarships, grants, student assistance programs like CalWORKs and EOPS for students' financial needs and those of their dependents, not to mention several other resources such as the financial aid, the veterans fund, and waivers. The college instructors have also become mindful of reducing textbook/material costs. A sizeable number of faculty have switched to either no-cost or low-cost courses by utilizing free and open sources for textbooks and courseware.

When so many support structures are in place with the addition of educational reforms that reduce the time, money, and effort in completing college successfully, it remains a mystery that the throughput rates are still unacceptably low. Students who were placed directly in transfer-level courses showed the highest failure and attrition, when compared to harder courses (support and pretransfer) which required additional time and effort. Despite the strides made in student access, student success seems to be elusive. It occurred to me as a researcher that the educational reforms are looking to validate student success by measuring student completion whereas in reality, there seems to be not enough motivation even when barriers to success were removed. This begs the question on what transpires in the classroom. As part of my proposed solutions, in tandem with the conceptual framework of this study based on Kuh's student success framework, I recommend that a thorough phenomenological study on classroom learning experience must be studied to triangulate the quantitative findings for a wholesome picture of the condition of education and throughput success.

Some of the solutions for immediate implementation are: to replace the current transfer-level courses for Statistics and Precalculus with the newly revised and recently approved courses for the same, strengthen the corequisite courses by switching from comingled to cohort model, and create linked, short-term, accelerated courses for the pretransfer-level to transfer-level sequence so that the completion time could be reduced from one year to one semester. These changes as well as the follow-up research undertakings can be fruitfully accomplished only with the buy-in of all the key stakeholders involved. Since it falls under the purview of the State and therefore funded by the taxpayer money, the institution is not only duty-bound but accountable as well to all the members it serves both directly and indirectly. As the world gets connected and competitive, it is imperative that our students are poised to enter confidently with rigor and purpose.

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[Using%20Disproportionate%20Impact%20Methods%20to%20Identify%20Equity%20Gaps.pdf](https://www.norcocollege.edu/academicAffairs/ie/ir/Documents/other/RP-Using%20Disproportionate%20Impact%20Methods%20to%20Identify%20Equity%20Gaps.pdf)

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Appendix A

Revised Placement Criteria at participating college for Statistics Pathway

High School GPA ^a	Additional Pre-requisites ^b	Placement Options
GPA \geq 3.0		Transfer-level Elementary Statistics
2.3 \leq GPA < 3.0	Passed the entire year of Algebra I or Integrated Math I	Transfer-level Elementary Statistics with co-requisite support
GPA < 2.3		One-level below transfer ^c

Note. ^a Cumulative high school GPA. ^b Any higher-level math course will also serve for these prerequisites.

^c Pre-Statistics or Intermediate Algebra for STEM or Intermediate Algebra for Liberal Arts.

Appendix B

Revised Placement Criteria at participating college for STEM Pathway

High School GPA ^a	Additional Pre-requisites ^b	Placement Options
$\text{GPA} \geq 3.4$	Passed Integrated Math III or Trigonometry	Transfer-level Precalculus
$2.6 \leq \text{GPA} < 3.4$	Passed the entire year of Algebra II/Trig or Integrated Math III	Transfer-level Precalculus with co-requisite support
$\text{GPA} < 2.6$	Passed the entire year of Algebra I or Integrated Math II	One-level below transfer ^c

Note. ^a Cumulative high school GPA. ^b Any higher-level math course will also serve for these prerequisites.

^c Intermediate Algebra for STEM.

Appendix C

Recommended AB 705 Placement Criteria for Statistics/ Liberal Arts Mathematics

High School Performance Metric	Recommended AB 705 Placement
HSGPA ≥ 3.0 Success Rate ^a = 75%	Transfer-level Elementary Statistics No additional academic or concurrent support required for students
$2.3 \leq \text{HSGPA} < 3.0$ Success Rate = 50%	Transfer-level Elementary Statistics Additional academic and concurrent support recommended for students
HSGPA < 2.3 Success Rate = 29%	Transfer-level Elementary Statistics Additional academic and concurrent support recommended for students

Note. This table has been modified from AB 705 memorandum released by Hope and Stankas (2018, pp. 6-7)

^a Colleges have not more than two years to innovate, validate their own innovations and compare the effectiveness of those designs to the tables above. The throughput for those innovations should meet or exceed the percentages in these tables for all students at similar levels of high school achievement (Hope & Stankas, 2018, p. 8).

Appendix D

Recommended AB 705 Placement Criteria for BSTEM Mathematics^a

High School Performance Metric	Recommended AB 705 Placement
HSGPA ≥ 3.4 OR HSGPA ≥ 2.6 AND enrolled in HS Calculus Success Rate ^b = 75%	Transfer-level BSTEM No additional academic or concurrent support required for students
HSGPA ≥ 2.6 OR enrolled in HS Precalculus Success Rate = 53%	Transfer-level BSTEM. Additional academic and concurrent support recommended for students
HSGPA ≤ 2.6 and no Precalculus Success Rate = 28%	Transfer-level BSTEM Additional academic and concurrent support recommended for students

Note. This table has been modified from AB 705 memorandum released by Hope and Stankas

(2018, pp. 6-7)

^aThe BSTEM table presumes student completion of Intermediate Algebra/Algebra 2, an equivalent such as Integrated Math III, or higher course in high school. Students who have not completed Algebra 2 or higher in high school but who enter college with intentions to major in STEM fields are rare. However, good practice suggests they should be informed that Algebra 2 is highly recommended as preparation for a STEM-oriented gateway mathematics course and that their likelihood of success will be higher in a statistics course (Hope & Stankas, 2018, p. 7).

^bColleges have not more than two years to innovate and validate their own innovations and compare the effectiveness of those designs to the tables above. The throughput for those innovations should meet or exceed the percentages in these tables for all students at similar levels of high school achievement (Hope & Stankas, 2018, p. 8).

Appendix E

MMAP Decision Tree Nodes by Transfer-Level Subject

Transfer-level Subject	Range 1 (lowest node)	Range 2 (all intermediate nodes)	Range 3 (all nodes w/ $\geq 70\%$ success rate)
English	HSGPA < 1.9	HSGPA ≥ 1.9 and < 2.6	HSGPA ≥ 2.6
Statistics	HSGPA < 2.3	HSGPA ≥ 2.3 and < 3.0	HSGPA ≥ 3.0
Precalculus	HSGPA < 2.6 and no Precalculus in HS	HSGPA ≥ 2.6 or Precalculus in HS	HSGPA ≥ 3.4 or 11 th grade HSGPA ≥ 2.6 with Calculus in HS

Source: Adapted from MMAP Research team (2018).

Appendix F

Placement in STEM pathway: By Demographics for Fall 2019 and Spring 2020

			Placement Level 1 ^a		Placement Level 2 ^b		Placement Level 3 ^c	
			(Direct)		(Coreq)		(Pretransfer)	
			%	N	%	N	%	N
Age	≤ 25 years	F'19	88.3%	53	92.7%	51	66.7%	2
	>25 years		11.7%	7	7.3%	4	33.3%	1
	≤ 25 years	S'20	72.5%	50	96.3%	26	0.0%	0
	>25 years		27.5%	19	3.7%	1	0.0%	0
Gender	Male	F'19	55.0%	33	58.2%	32	100.0%	3
	Female		45.0%	27	41.8%	23	0.0%	0
	Male	S'20	52.2%	36	48.1%	13	0.0%	0
	Female		47.8%	33	51.9%	14	0.0%	0
Ethnicity	Hispanic/Latino	F'19	45.0%	27	60.0%	33	66.7%	2
	Not Hispanic/Lat		45.0%	27	18.2%	10	33.3%	1
	No Response		10.0%	6	21.8%	12	0.0%	0
	Hispanic/Latino	S'20	52.2%	36	48.1%	13	0.0%	0
	Not Hispanic/Lat		31.9%	22	18.5%	5	0.0%	0
	No Response		15.9%	11	33.3%	9	0.0%	0

Note. N provides the count of the students placed in the specified categories.

- a. Starting at transfer-level with no support course based on multiple measures
- b. Starting at transfer-level with mandatory corequisite support course based on multiple measures
- c. Starting one level below transfer-level based on multiple measures

Appendix G

Placement in Non-STEM pathway: By Demographics for Fall 2019 and Spring 2020

			Placement Level 1 ^a		Placement Level 2 ^b		Placement Level 3 ^c	
			(Direct)		(Coreq)		(Pretransfer)	
			%	N	%	N	%	N
Age	≤ 25 years	F'19	81.9%	312	85.3%	122	76.1%	35
	>25 years		18.1%	69	14.7%	21	23.9%	11
	≤ 25 years	S'20	74.0%	293	85.0%	113	100.0%	2
	>25 years		26.0%	103	15.0%	20	0.0%	0
Gender	Male	F'19	35.4%	135	37.1%	53	37.0%	17
	Female		64.6%	246	62.9%	90	63.0%	29
	Male	S'20	33.6%	133	39.1%	52	0.0%	0
	Female		66.4%	263	60.9%	81	100.0%	2
Ethnicity	Hispanic/Latino	F'19	54.6%	208	54.5%	78	54.3%	25
	Not Hispanic/Lat		29.9%	114	28.7%	41	28.3%	13
	No Response		15.5%	59	16.8%	24	17.4%	8
	Hispanic/Latino	S'20	54.3%	215	49.6%	66	100.0%	2
	Not Hispanic/Lat		34.8%	138	29.3%	39	0.0%	0
	No Response		10.9%	43	21.1%	28	0.0%	0

Note. N provides the count of the students placed in the specified categories.

- a. Starting at transfer-level with no support course based on multiple measures
- b. Starting at transfer-level with mandatory corequisite support course based on multiple measures
- c. Starting one level below transfer-level based on multiple measures

Appendix H

Placement in STEM pathway: By Status for Fall 2019 and Spring 2020

			Placement Level 1		Placement Level 2		Placement Level 3	
			(Direct)		(Coreq)		(Pretransfer)	
			%	N	%	N	%	N
Throughput Status	Passed	F'19	34.3%	60	55.0%	55	100.0%	3
	Failed		32.0%	56	25.0%	25	0.0%	0
	Dropped		33.7%	59	20.0%	20	0.0%	0
	Passed		39.2%	69	39.1%	27	0.0%	0
	Failed	S'20	33.5%	59	39.1%	27	0.0%	0
	Dropped		27.3%	48	21.7%	15	100%	1
DSPS Status	Yes	F'19	1.7%	1	7.3%	4	0.0%	0
	No		98.3%	59	92.7%	51	100.0%	3
	Yes	S'20	7.2%	5	7.4%	2	0.0%	0
	No		92.8%	64	92.6%	25	0.0%	0
EOPS Status	Yes	F'19	5.0%	3	10.9%	6	0.0%	0
	No		95.0%	57	89.1%	49	100.0%	3
	Yes	S'20	14.5%	10	3.7%	1	0.0%	0
	No		85.5%	59	96.3%	26	0.0%	0
CalWORKs Status	Yes	F'19	3.3%	2	0.0%	0	0.0%	0
	No		96.7%	58	100.0%	55	100.0%	3
	Yes	S'20	0.0%	0	0.0%	0	0.0%	0
	No		100.0%	69	100.0%	27	0.0%	0

Note. N provides the count of the students placed in the specified categories.

DSPS stands for Disability Students Program & Services

EOPS stands for Extended Opportunity Programs & Services

CalWORKs stands for California Work Opportunity & Responsibility to Kids

Appendix I

Placement in Non-STEM pathway: By Status for Fall 2019 and Spring 2020

			Placement Level 1 (Direct)		Placement Level 2 (Coreq)		Placement Level 3 (Pretransfer)	
			%	N	%	N	%	N
Throughput Status	Passed		42.6%	381	41.4%	143	48.9%	46
	Failed	F'19	43.7%	391	36.5%	126	39.4%	37
	Dropped		13.7%	123	22.0%	76	11.7%	11
	Passed		48.1%	396	41.7%	133	6.7%	2
	Failed	S'20	39.5%	325	30.4%	97	20.0%	6
	Dropped		12.4%	102	27.9%	89	73.3%	22
DSPS Status	Yes	F'19	3.7%	14	6.3%	9	4.3%	2
	No		96.3%	367	93.7%	134	95.7%	44
	Yes	S'20	4.3%	17	11.3%	15	0.0%	0
	No		95.7%	379	88.7%	118	100.0%	2
EOPS Status	Yes	F'19	9.7%	37	16.8%	24	19.6%	9
	No		90.3%	344	83.2%	119	80.4%	37
	Yes	S'20	11.9%	47	16.5%	22	100.0%	2
	No		88.1%	349	83.5%	111	0.0%	0
CalWORKs Status	Yes	F'19	1.6%	6	2.1%	3	0.0%	0
	No		98.4%	375	97.9%	140	100.0%	46
	Yes	S'20	1.3%	5	2.3%	3	0.0%	0
	No		98.7%	391	97.7%	130	100.0%	2

Note. N provides the count of the students placed in the specified categories.

DSPS stands for Disability Students Program & Services

EOPS stands for Extended Opportunity Programs & Services

CalWORKs stands for California Work Opportunity & Responsibility to Kids

Appendix J

IRB Approval from Creighton University



DATE:	17-Jun-2020
TO:	Albert, Maria
FROM:	Social / Behavioral IRB Board
PROJECT TITLE:	A causal-comparative study on throughput success rates of transfer-level mathematics students post-AB 705 implementation in California community colleges
REFERENCE #:	2001110-01
SUBMISSION TYPE:	Initial Application
REVIEW TYPE	Exempt
ACTION:	APPROVED
EFFECTIVE DATE:	17-Jun-2020

Thank you for your Initial Application submission materials for this project. The following items were reviewed with this submission:

- Creighton University HS eForm
 - Research_Protocol_Maria_Radhika_Albert
 - Data Collection Sheet - Maria Radhika Albert

This project has been determined to be exempt from Federal Policy for Protection of Human Subjects as per 45CFR46.101 (b) 4.

All protocol amendments and changes are to be submitted to the IRB and may not be implemented until approved by the IRB. Please use the modification form when submitting changes.

If you have any questions, please contact the IRB Office at 402-280-2126 or irb@creighton.edu. Please include your project title and number in all correspondence with this committee.

Institutional Review Board

☎ 402.280.2126 | ☎ 402.280.3200

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