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Comprehensive, Powerful, Academic Database (CPAD): An Evaluative Study Of A Predictive Tool Designed For Elementary School Personnel In Identifying At-Risk Students Through Progress, Curriculum, And Performance Monitoring

Sarah Jo Chavez-Gibson
University of Texas at El Paso, sjchave1@gmail.com

THE COMPREHENSIVE, POWERFUL, ACADEMIC DATABASE (CPAD): AN EVALUATIVE STUDY OF A PREDICTIVE TOOL DESIGNED FOR ELEMENTARY SCHOOL PERSONNEL IN IDENTIFYING AT-RISK STUDENTS THROUGH PROGRESS, CURRICULUM, AND PERFORMANCE MONITORING

SARAH CHAVEZ-GIBSON

Department of Educational Leadership and Foundations

APPROVED:

Richard Sorenson, Ed.D., Chair

Maria Teresa Cortez, Ed.D.

Rodolfo Rincones, Ph.D.

Judith Munter, Ph.D.

Benjamin C. Flores, Ph.D.
Dean of the Graduate School

Dedication

This dissertation is dedicated to to my parents, Herbert and Mary Chavez: Thank you for your patience, support, and unconditional love. You both have taught me to be a strong independent woman.

To my Dad that taught me how to be strong, truthful, and understanding and that a "handshake" is as good as a contract. The years of working on our cattle ranch instilled a humbleness that will never waver or be forgotten. I love you more than I could ever express in this lifetime, and know that it is your tenacity that you showed me how to live life that carries me through today, tomorrow, and forever.

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Abstract

The purpose of this study is to exam in-depth, the Comprehensive, Powerful, Academic Database (CPAD), a data decision-making tool that determines and identifies students at-risk of dropping out of school, and how the CPAD assists administrators and teachers at an elementary campus to monitor progress, curriculum, and performance to improve student skills and academic assessment results. This study provides an in-depth examination and evaluation of the Comprehensive, Powerful, Academic Database (CPAD) as the predictive modeling tool utilized at each of the campuses researched. Predictive modeling tools utilized at various educational institutions throughout the United States, reviewed within the study, facilitate the understanding of which at-risk indicators are necessary to predict student academic achievement in elementary school levels.

The CPAD in comparison with other predictive models, utilizing and incorporating the same exact established at-risk indicator criteria is illustrated in a chart of the reviewed predictive modeling databases and their serviceable abilities to meet state and federal at-risk student indicator standards, Appendix (1). Predictive modeling tools and database qualities discussed in the study, will guide the reader in understanding elements and components necessary for predicting elementary school at-risk students. Organization procedures in implementing CPAD at these campuses are explained within the study, as well as a logic model developed to enhance in clarification of the complexity of the strategies and processes of CPAD, Appendix (3-9). Results from the implementation of CPAD for each of the three elementary campuses are also examined within the study.

The Table of Contents reveals the storyboard of the research which affords the reader the opportunity to follow the examination and evaluation of the CPAD database strategies,

procedures, and processes. Many of the components of each major heading have sub-headings as a means of examining and evaluating each major heading. Sub-headings that utilize sub/sub-headings were utilized to better assist the reader in the examination and evaluation of the listed components.

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Chapter 1: Introduction

The United States struggles with growing numbers of high school dropouts (Brewer, 2005, p. 1). Policymakers at every level must aid all public education institutions with the difficult task of finding and supporting proven strategies and effective programs that significantly reduce dropout rates and improve graduation rates. According to the National High School Center (NHSC) as schools adopt strategies for dropout prevention, districts need to provide parallel initiatives to include turnaround plans and models for low-performing schools that include data based needs assessments with success indicators for determining student progress and achievement (Monrad, 2007). Early warning systems allow schools to capture the actual scope of the dropout challenge, one student at a time. State, district, and school leaders need to exert their political will to stand by transparent, accessible, accurate, and usable data systems designed to address meaningful approaches to dropout prevention. Students at-risk of dropping out and who are identified early, monitored closely, and supported appropriately are more likely to stay in school (Ardoin, 2006; Crawford, Tindal, & Stieber, 2001; Green & Alderman, 2004; Jerald, 2006; Shinn, 2007). The fact that the high school "dropout problem" is an ever-increasing issue supports the notion that not enough emphasis is placed on early meaningful identification (Dynarski, 2008; Pinkus, 2008). Part of the problem relates to the fact that early data warning systems are limited, not regularly implemented, and lack depth and meaning.

A review of the literature reveals that many researchers have focused heavily on high school graduation rates as well as students who fall into at-risk categories (Mohammed, 2008; Monrad, 2007; Shankland, 2010). Predictive modeling tools using at-risk indicators should be a determining factor to assist administrators and teachers in finding ways to help high school

students graduate and become productive citizens. This argument pleads: “Why should educators wait until high school to determine the level of success and the monitoring of progress and performance for students?” While it is never too late to help students succeed, late identification and intervention is reactive. The belief that “an ounce of prevention is worth a pound of cure” is applicable through an early prevention program that uses purposeful identification, and consequential intervention. This should become a common practice in public schools in order to lower the high rate of high school dropouts. The entire premise behind each of the research tools is to monitor student progress and performance. This will help administrators and teachers take on a role of using data to determine exactly where student levels are, in every subject, and by objective. By equipping teachers with these tools, they will be able to use such data analysis in relation to student expectations and outcomes.

Administrators and teachers are continuously met with high demands to increase scores for state and federal accountability. Not only is the rigor of accountability systems increasing, so is the rigor and level of new state assessments. Even with new and more rigorous state assessments, the federal accountability system is demanding success and high passing rates on first year implementation. Setting exceptionally high standards for students from the beginning of their educational careers, and establishing standards across every subject is crucial. “Setting high standards is the first step in a process that must also include teachers’ use of curricular materials and instructional strategies that lead to increased achievement levels” (Stecker, Lembke, & Foegen, 2008, p. 48). Students who are unable to meet the demands of new rigorous assessments will not graduate (Brewer, 2005). Therefore, it is imperative that a research tool be developed at the elementary level to track student progress and performance to ensure that

students are academically prepared, and those who are not, are identified, and placed into intervention programs so that they can later meet and exceed expectations.

A continuous struggle to determine the valid use and recognition of a monitoring tool, that will facilitate in identifying and detecting elementary students who may be potentially at-risk for dropping out of high school, has not yet been designed and/or properly analyzed (Crawford, Tindal, & Stieber, 2001; Green & Alderman, 2004; Monrad, 2007; Shinn, 2007). Little research in this area has been conducted and the need for an effective monitoring tool at the elementary level to identify students projected of dropping out of school, using local at-risk indicators, is warranted. This is crucially clear when considering and exploring factors associated with dropout rates through longitudinal analysis (Monrad, 2007; Stecker, Fuchs, & Fuchs, 2008; Stecker, Lembke, & Foegen, 2008; Wallace, Espin, McMaster, Deno, & Foegen, 2007, p. 90).

This study will incorporate a quantitative methodology in approaching the examination and evaluation of a predictive modeling tool, which would suit elementary schools in detecting and identifying at-risk students. Administrators and teachers at the elementary level need a tool that can identify potentially at-risk students, and predict academic success through monitoring students' progress and performance. These results would be based on local assessments that replicate state assessments. Different models of databases presented throughout this study all have abilities that can identify data, sort said data into categories, and then, compare and formulate data into information. The premise of this study is to examine a predictive modeling tool that will be useful to campus administration and teachers at the elementary level, to determine the response relative to intervening for the benefit of at-risk students. This early

warning system must permit elementary administration and teachers to focus on student academic achievement and success.

As presented in Chapter Two: A Review of the Literature, it is evident that research centers and educational agencies use predictive models to create useful tools to bridge the gap between research and practice. The purpose of this study is to examine, in-depth, the Comprehensive, Powerful, Academic Database (CPAD). The CPAD will be examined through the lens of a practitioner and researcher. This predictive model, as examined within this study, permits the reader an understanding of a database that incorporates data collection and statistical analysis, which in turn is used to predict student academic success.

Other databases reviewed for this study were the most widely found predictive models incorporating scientific based-research, which predicted student academic success. An examination of these models, and a thorough analysis of the relevant research-based literature, demonstrated that the CPAD had similar at-risk indicators and associated assessment-oriented identifiers. Each database was further analyzed by a process that allowed for the creation of a matrix listing of at-risk indicator criteria (see Appendix 1). Beneath each listed database, a checkmark was placed if it met the at-risk indicator criteria, and is presented in an at-risk indicator informational chart, (see APPENDIX 1).

Databases examined include: Dynamic Indicators of Basic Early Literacy Skills (DIBELS), Texas Education Agency (TEA) Lonestar Report, National Educational Data Model (NEDM), Southwest Educational Development Laboratory (SEDL), Research and Development (RAND) Data Driven Decision Making (DDDM), Statewide Longitudinal Data Systems (SLDS), Early Warning Data System (EWDS), and Comprehensive, Powerful, Academic Data (CPAD). Furthermore, Chapter Two: Review of the Literature, will examine elements and components

that are relevant to provide background information to the reader on predictive modeling, at-risk and on-target student indications, predictive modeling tools used in elementary to college levels, and monitoring through progress, curriculum, and performance. Finally, an examination and evaluation of CPAD with its components and elements is also presented in APPENDIX (3-9).

A brief description of these databases are as follows, and a rubric of their capabilities are located in the appendices. DIBELS is a database that enables administrators and teachers to identify students that may need facilitation in literacy. TEA Lonestar Report is a database that provides data for Texas schools on enrollment, accountability, graduation, and high school completion. NEDM database is a theoretical but detailed representation of the education information domain. The Education Data Model shares understanding among all education stakeholders as to what information needs to be collected and managed. SEDL provides technical support services for increasing the capacity of educators and organizations to conduct research and evaluation. RAND has many facets as to help improve policy and decision making through research and analysis. SLDS is designed to help teachers make informed decisions to improve student learning. EWDS tool was originally developed by the National High School Center (NHSC) at the American Institutes for Research (AIR) to calculate automatically the high-yield indicators related to dropout.

1.1 Central Theme/Background

Through the examination and evaluation of the CPAD, important indicators are identified for elementary schools to consider in determining a student's level of academic success. These indicators are based on state assessments, school district created local common assessments, reflecting state and federal standards, and common assessments usually administered weekly to assess student academic success over a period of time. Other local indicators include "mock"

tests that typically resemble state accountability exams administered to determine how much of the curriculum students have acquired or mastered, and if students are performing at the mastery level. “Mock” tests also serve as effective methods by which students can build stamina for state initiated testing days, and serves as formulated calculations of what determines the predictive abilities of the CPAD. “Benchmark” testing is another local assessment that determines student academic growth and frequently predicts how a student may perform on a state exam. Each of these local assessments is an indicative approach or model to help predict student academic progress and performance. However, for this study’s purpose, an in-depth examination and evaluation of how the CPAD predictive abilities identify at-risk students through each process, output, and outcome is detailed in Chapter Two: Review of the Literature.

Students in elementary school can be potential at-risk candidates for dropping out of high school (Jerald, 2006; Monrad, 2007). Indicators such as failure to be promoted, excessive absenteeism, disengagement, low performance, abused and neglected students, behavior, and mobility serve as key factors that identify students at-risk of academic failure. These indicators are necessary in monitoring and identifying at-risk students using an early warning system tool. The elementary level is key in identifying these students in order to produce productive middle and high school students. Since elementary level education is preparation for later level achievement, administrators and teachers must ensure that students have the foundational intervention skills and strategies to be successful in middle and high school.

According to the National High School Center (NHSC), more research is needed relative to dropout prevention programs and strategies (Monrad, 2007). More importantly, early detection warning systems are highly recommended and needed at the elementary level. Identifying students at-risk of dropping out of school by using an early warning system is only

the first step in addressing the dropout challenge. "The first step in a proactive approach to stemming dropout is to build an early warning system, designed to use accurate data to help target an appropriate mix of interventions for groups and individual students. Such an electronic data system includes individual student-level data that can track students over time and also allow risk factors to be assessed" (Jerald, 2006, p.10). Studying the indicators made readily available by the early warning system can help school officials target students in need and then provide appropriate interventions. The next step is to identify and provide effective and appropriate dropout-prevention strategies. Predictive models that have the ability to track local at-risk indicators are crucial in the development and maintenance of student academic success.

One such predictive early warning model was developed locally and designed to predict student progress and performance. Marie Yarberry developed the warning system design, the Comprehensive, Powerful, Academic Database (CPAD), early in her educational career. Marie Yarberry began her educational career as a pre-kindergarten teacher; and held positions of at-risk coordinator, assistant principal, principal at the elementary level, and director of elementary, middle and high schools. Her extensive and impressive background enabled her to be an expert in the field of education. Marie Yarberry developed this database from a Microsoft Excel Spreadsheet, which incorporated all demographic, Texas Public Education Information Management System (PEIMS) information, and common assessments on all students, most notably those that were in the grade levels counted for state and federal accountability. Marie Yarberry recognized data reports offered from school district officials, the Texas Education Agency (TEA), and other data collection sources, individually contained information she collected for predictive purposes. However, each data report did not afford the opportunity to monitor student's progress by quickly collecting, sorting, and filtering information specific to the

students and school in one convenient location. The lack of having one source to acquire all the data and information further complicated the problem of monitoring all at-risk student indicators in a meaningful way. Due to each individual report from each education agency or data source, the amount of data, as well as fragmented data that administrators and teachers had to disaggregate, further complicated the monitoring process. Such made it even more difficult to cross-compare information. Thus, Marie Yarberry created the CPAD to ensure a "one-stop shop" for monitoring students based on state and federal at-risk indicators, as well as monitoring student academic results based on mock assessments.

This scholar-practitioner has personally utilized CPAD and has seen results with the students and overall state and federal assessment results. By incorporating the CPAD the researcher and practitioner has firsthand knowledge of the predictive model and its strategies and procedural capabilities.

The CPAD is designed to offer a level of detection and warning to administrators and teachers for students at-risk of failure at the elementary, middle, and high school levels. The CPAD is also designed to identify students that are on target and aid administrators and teachers in guiding students to surpass minimum standards and achieve commended performance on state assessments.

1.2 Statement of the Problem

Local campus administrators have many roles and responsibilities. The administrative position is one in which the leader is frequently the manager of people, facilities, programs, and more. However, most importantly the role is one of leadership whereby administrators must ensure that students are learning and are successful in their academic achievement. The difficulties faced by campus administrators in identifying at-risk students far too often relates to

their inability to track student progress and performance in a consistent and constant manner to best provide teachers with the opportunities to make data-based decisions. Furthermore, tools that easily track the effectiveness of interventions are questionable (Ardoin, 2006; Lab, 2009; Marsh, 2011). Many administrative reports are available with results and information accessible by administrators and teachers. However, reviewing over twenty reports to determine the same information utilized and incorporated within one predictive model, saves time and energy in monitoring student academic progress. Useful early monitoring and predictive models to aid in the detection of at-risk students is essential at the elementary school level (Pinkus, 2008; Dynarski, 2008; Hammond, 2007). Finding such a tool for campus administrators and teachers to incorporate as a useful and beneficial predictive model for everyday use at the local campus is all too often difficult. Many predictive models have been utilized by schools; however, finding the right model for administrators and teachers to incorporate has seldom been easy, especially at the elementary school level.

1.3 Purpose of the Study/Project

One of the most critical steps in overcoming the dropout problem is to select a database by which longitudinal analysis can identify at-risk students in need, and further, identify students that have the ability to reach commended academic achievement performance. According to the National High School Center (Monrad, 2007), much of the research conducted relates to high school dropout indicators and the necessity to develop early warning databases, as it is necessary to have an early warning sign system in place. Tracking elementary student progress and performance will aid in determining which at-risk students need intervention, as a means of assisting these students in attaining academic achievement, thus avoiding dropping out during their secondary school years.

This study will examine and evaluate the processes, outputs, and outcomes of the Comprehensive Powerful Academic Data (CPAD) which is a database that individualizes fragmented data from other sources, predicts success/failure rates, and implements strategies and procedures for identifying, and intervening for student academic success and administrator and teacher meaningful professional development. The CPAD is a predictive tool utilized as an early warning system in the detection of elementary school student academic success. The CPAD is useful for administrators and teachers at elementary school levels to determine interventions that are necessary for at-risk student's academic success, as well as facilitates teacher preparedness in understanding and making data driven decisions for their students. The in-depth examination and evaluation of the CPAD, and its strategies and procedures for responses to intervention will be the objective of this study. This study will also detail how the CPAD incorporates local, state, and federal indicators of student progress, and performance utilized and established by existing predictive modeling databases for identifying at-risk student's at all educational levels. This study analyzes and describes the logical approach in illustrating a logic model to visualize CPAD, and utilizes scientific research data to quantify student academic success. The Statistical Package for the Social Sciences (SPSS, 2012) software will assist the researcher in further determining the predictive abilities of the CPAD, its strategies and procedures through which the data consists of a cohort of students over a longitudinal analysis from calculations based on state assessment scores.

The examination and evaluation of the CPAD utilized at each research site and the incorporation of the CPAD strategies and procedures to track student progress and performance determines the initiation of the response to intervention relative to the at-risk students that need specific, meaningful interventional strategies.

1.4 Need for the Study/Project

While there are many predictive models in place that signify and represent different settings, there is a need for a predictive model for elementary school at-risk students. Many predictive models are used across many practice settings. Predictive models are utilized by health, marketing, business, technical, and other professional settings. "Each predictive model is a technological tool that functions as an electronic claims canvasser searching for predefined variables of interest to identify, provide, and utilize data driven decision making by targeting specific interventions. The true value lies in the thorough evaluation of the outcomes by utilizing a combination of specific data and evidence-based interventions leading to improved outcomes" (Hodgman, 2008, p. 19). Therefore, the greatest need of this study was an examination and evaluation of the CPAD, its strategies and procedures to assist administrators and teachers in the early detection of elementary school at-risk students through the processes of its predictive modeling capabilities.

1.5 Research Questions

This study utilized a quantitative approach through the examination and evaluation of the CPAD by means of a logic model methodology examined in detail in Chapter Two. The CPAD, as a predictive modeling tool by campus administrators and teachers is designed to identify potentially at-risk elementary school students, and further predict academic success through monitoring progress and performance via local assessments that replicate state assessment instruments. The CPAD is also designed to provide meaningful and structured responses to intervention. The research questions associated with this study are as follows:

1. How is the CPAD organized and what does it look like?

2. Through identifying the processes of the CPAD logic model, do the CPAD processes model an effective tool in determining outcomes for an elementary school student's academic achievement as in comparison to other predictive modeling tools reviewed?
3. Through what processes does the CPAD predictive model effectively determine, at an elementary school level, a student's at-risk potential of dropping out of school?
4. In evaluating the CPAD, as an early warning predictive model, does it facilitate administrators and teachers as a data decision-making tool in the process of identifying at-risk and potentially at-risk students in elementary grade levels?
    a. As a data decision-making tool, does the CPAD consist of most if not all at-risk indicators, demographics, historical data, and diagnostic test results which can be used to detect at-risk students?
    b. As a data decision-making tool, does the CPAD identify at-risk students from each tested grade level and each tested subject to predict student mastery/non-mastery, and how the results are communicated?
    c. As a data decision-making tool, does the CPAD and its processes and procedures of implementation identify key components, which pinpoint beneficial and meaningful interventions?

1.6 Theoretical Framework(S) Underlying the Research Purpose

The purpose of this study is to exam in-depth, the Comprehensive, Powerful, Academic Database (CPAD), a data decision-making tool that determines and identifies students at-risk of dropping out of school, and how the CPAD assists administrators and teachers at an elementary school to monitor progress, curriculum, and performance to improve student skills and academic assessment results. According to Smyth (2004), (Reichel, 1987) developed a conceptual

framework and defined it as a set of broad ideas and principles taken from relevant fields of inquiry and used to structure a subsequent presentation. Smyth (2004) suggests that a conceptual framework has potential usefulness as a tool to scaffold research and, therefore, assist a researcher to make meaning of subsequent findings. Such a framework should be intended as a starting point for reflection about the research and its context. The framework is a research tool intended to assist a researcher to develop awareness and understanding of the situation under scrutiny.

Smyth (2004) examined a study by (Mason, 1996) which listed expectations for developing and incorporating research frameworks following three steps:

(1) the framework is a construction of knowledge bound by the life-world experiences of the person developing it;

(2) the nature of a conceptual framework means that it consciously or unconsciously informs thought and practice by increasing personal sensitivity to notice particular occurrences so this must be accounted for; and

(3) no researcher can expect that all data will be analyzed using the framework without the risk of limiting the results from the investigation.

For the purpose of this study, the theoretical framework, which is detailed in Chapter 2, is encased within a developed logic model which details how CPAD works to identify students at the elementary school level at-risk of dropping out of school, thus further ensuring that said students are effectively monitored to best achieve academic success.

1.6.A Definition of Terms

The definitions of terms utilized are primarily to afford the reader, which may not be familiar with educational acronyms and verbiage, an understanding of items that may not be familiar or common across other disciplines.

AYP: Under the accountability, provisions in the No Child Left Behind (NCLB) Act, all public school campuses, school districts, and the state are evaluated for Adequate Yearly Progress (AYP). Districts, campuses, and the state are required to meet AYP criteria on three measures: Reading/Language Arts, Mathematics, and either Graduation Rate (for high schools and districts) or Attendance Rate (for elementary and middle/junior high schools). If a campus, district, or state that is receiving Title I, Part A funds fail to meet AYP for two consecutive years, that campus, district, or state is subject to certain requirements such as offering supplemental education services, offering school choice, and/or taking corrective actions (Texas, Texas Education Agency, 2012).

CBM: Curriculum Based Monitoring better known as Curriculum Based Measurement is a method of monitoring student educational progress through direct assessment of academic skills (Allinder, Bolling, Oats, & Gagnon, 2000; Espin, 2005; Fuchs, 2004).

ELL: English Language Learners indicates a person who is in the process of acquiring English and has a first language other than English (Texas, Texas Education Agency Definition of Terms, 2011).

High-stakes testing: is a testing process with important consequences for the test taker (Texas, Texas Education Agency Definition of Terms, 2011).

LEP (Limited English Proficiency): Individuals with a primary or home language other than English who must, due to limited fluency in English, communicate in that primary or home

language if the individuals are to have an equal opportunity to participate effectively in or benefit from any aid, service or benefit provided by the transportation provider or other DOT recipient (Texas, Texas Education Agency Definition of Terms, 2011).

Multivariate analysis: a generic term for any statistical technique used to analyze data from more than one variable (Ardoin, 2009; BusinessDictionary.com, 2011).

NCLB: No Child Left Behind Act, 2001 (Texas, Texas Education Agency Definition of Terms, 2011).

Performance Based Monitoring: Using a data-driven, performance-based model to observe, evaluate, and report on the public education system at the individual student group, campus, local education agency, regional, and statewide levels across diverse areas including program effectiveness; compliance with federal and state law and regulations; financial management; and data accuracy for the purpose of assessing that student needs are being met; promoting diagnostic and evaluative systems in local education agencies (LEAs). All these issues are integrated with the agency's desk audit and intervention process, which then relies on a research, based framework of interventions that ensure compliance and enhance student success (Shinn, 2007; Agency, 2010).

Progress Based Monitoring: A scientifically based practice that is used to assess students' academic performance and evaluate the effectiveness of instruction (Deno, Reschily, Lembke, Magnusson, Callender, Windram, & Stachel, 2009; Foegen, Jiban, & Deno, 2007).

PEIMS: Public Education Information Management System encompasses all data requested and received by TEA about public education, including student demographic and academic performance, personnel, financial, and organizational information (Texas, Texas Education Agency Definition of Terms, 2011).

Predictive Model/ing: Predictive modeling is the process by which a model is created or chosen to best predict the probability of an outcome (Hodgman, 2008; Steen, 1994).

Response to Intervention (RTI): A method of academic intervention. RTI is the practice of meeting the academic and behavioral needs of all students through a variety of services containing the following key elements.

- High-quality instruction and scientific research-based tiered interventions aligned with individual student need.
- Frequent monitoring of student progress to make results-based academic and/or behavioral decisions.
- Application of student response data to important educational decisions (student placement, intervention, curriculum, and instructional goals and methodologies) (Texas, Texas Education Agency, 2012).

SPED: Special Education is the education of students with special needs in a way that addresses the students' individual differences and needs (United, Department of Education ED Data Express, 2011).

State of Texas Assessment of Academic Readiness (STAAR): State of Texas Assessments of Academic Readiness replaced the Texas Assessment of Knowledge and Skills (TAKS). (Texas, Texas Education Agency, 2012).

Texas Assessment Knowledge and Skills (TAKS): Assessment designed to measure the extent to which a student has learned and is able to apply the state defined knowledge and skills at each tested grade level (Texas, Texas Education Agency, 2012).

TAKS Commended performance: A percentage of students performing at or above the commended level on the TAKS test in a given subject area (Texas, Texas Education Agency, 2012).

Texas Education Code (TEC): set of the state statutes (laws) governing public education in Texas. It applies to all educational institutions supported in whole or in part by state tax funds, unless specifically excluded by the code. The TEC directs the goals and framework of public education in Texas. The Texas Legislature establishes the code (Texas, Texas Education Agency Definition of Terms, 2011).

Texas Essential Knowledge and Skills (TEKS): The TEKS are the state standards for what students should learn and be able to achieve (Texas, Texas Education Agency Definition of Terms, 2011).

Comprehensive, Powerful, Academic Data (CPAD): Comprehensive, Powerful, Academic Data supports the belief that schools should operate with efficient, systematic, collaborative, and structured means of examining the core elements of student risk and achievement. These indicators are then analyzed in a manner that utilizes comprehensive data and presentation techniques that are based on brain research.

Texas Primary Reading Inventory (TPRI): is an assessment tool of a student's reading/language arts development. (Texas, Texas Education Agency Definition of Terms, 2011).

Univariate analysis: Techniques of multivariate analysis that can be used when analyzing variation in a data set in which there is only a single variable parameter of interest (Ardoin & Christ, Curriculum-Based Measurement of Oral Reading: Standards Errors Associated With

Progress Monitoring Outcomes From DIBELS, AIMSweb, and an Experimental Passage Set, 2009).

1.7 Organization of the Chapters

Chapter One introduces the need of utilizing an early warning detection system for elementary students and suggests that the CPAD would constitute as a predictive model for student progress and performance monitoring.

Chapter Two presents the review of related literature. The review includes the following topics: predictive modeling elements, components of predicting at-risk and on-target students, and monitoring through the three processes of performance, curriculum, and progress. Predictive models, brief discussion of databases, and the in-depth examination and evaluation of CPAD are also included in Chapter Two.

Chapter Three follows a logic model methodology that utilizes methods presented to the reader on why CPAD works. Additionally, Chapter Three presents statistically analyzed scale scores of elementary school students. Included within this chapter is the methodological approaches incorporated to include a logic model to illustrate what CPAD is capable of predicting student academic success. The quantitative approach will review, through the analysis of SPSS statistical software. Incorporating a 2x2x3 repeated measures, or multivariate analysis ANOVA, in which groups are compared with one dependent variable over time.

Chapter Four consists of the results of data relative to students lexile/quantile scale scores from the researched sites as well as the presentation of CPAD logic model.

Chapter Five is the data collected from each subject at each of the researched sites. Implications and findings of the study are revealed, along with a reflective analysis of the data

collected. This chapter will provide results based on the collection of information from Chapter Four. In conclusion, future research will be discussed.

1.8 Summary

The need for an elementary school level early warning detection system is desirable to identify at-risk students and reveal the importance of acquiring information on students exhibiting indications of at-risk performance earlier rather than to offset the ever-growing numbers of high school dropouts. An early warning detection system is needed to identify students that have the ability to achieve academic commended performance on state assessments. It is imperative that administrators and teachers empower and take responsibility at every level of education, most notably as related to rectifying the continuous growth of at-risk students.

At-risk students do not become at-risk in high school; there is a conclusively high probability that high school at-risk students have been at-risk since elementary school (Foundation, 2009; Hammond, Linton, Smink, & Drew, 2007). This study examines, in-depth, the CPAD, utilizing a theory of action to develop a logic model methodology, and illustrate activities that relate to outcomes. The purpose of CPAD is to monitor every student and every data point, so that individual students are successful early on thereby decreasing the likelihood of dropping out of high school. The immediate and long-term outcomes of CPAD will be further examined in Chapter Two.

Chapter 2: Review of the Literature

2.1 Introduction

In the state of Texas, research has been conducted on the capacity of prisons with new prisons being built based on the number of students that fail the state assessments in the 3rd and 4th grade levels (Ellis, 2004). This profound statement must be addressed by educational reform. Not creating programs and strategies to combat high school dropout rates and addressing at-risk students is detrimental to the advancement of the United States. Completion of high school is required for accessing postsecondary education and is a minimum requirement for most jobs. According to Laird, Lew, Debell, and Chapman, (2001) cocited in *Child Trends Databank* (2008), higher income and occupational status is attributed to receiving a high school diploma. The status of the United States as a world leader is determined by the production of highly professional and educated individuals (Laird, Lew, Debell, & and Chapman, 2001). The most fundamental step to solving this educational concern is building a database that can longitudinally identify at-risk students in need. According to the National High School Center (Monrad, 2007), much of the current research is on high school dropout indicators and there is a need to develop an early warning system for the elementary grade levels.

Such a predictive model through performance, curriculum, and progress monitoring at the elementary school level is crucial in the fight against increasing dropout rates in high schools. It is imperative that administrators and teachers understand that tracking student progress in the elementary years will ultimately help reduce the at-risk population. Many concepts can be borrowed from settings other than education, such as technological, health, and business that also use predictive modeling to identify weaknesses and intervene when and where needed. "Such data could assist jurisdictions in identifying populations of students in need of intervention and in

evaluating the success of their efforts to intervene" (Technologies, 2008, p. 6). Thus, school districts can also develop early warning systems to help them identify students in need of extra academic or other support systems making it possible for strong partnerships with elementary schools to ensure that students stay on track. These actions can and should begin much earlier than high school and be targeted and individualized by taking advantage of predictive modeling (Technologies, 2008).

This review of literature will examine elements and components that facilitate in understanding predictive modeling, student at-risk indicators, monitoring of student academic success, and the in-depth examination and evaluation of CPAD.

2.2 Predictive Modeling

A review of some of the predictive models utilized in educational reform across the United States is examined in this chapter. Understanding of data and making sense of the data collected is usually the most difficult to distinguish and disseminate to individuals who want clear and precise information to aid them in making effective student-centered decisions. Many levels of data are collected, and making heads or tails of the enormous amounts of data collected from many entities and sources must be easily filtered into a process that can be useful and predictive (Fayyad, 1996, p. 37).

Predictive models used to track the progress and performance of students, not only are incorporated for this specific use, they also guide stakeholders towards the accountability measures imposed by state and federal guidelines, as well as local levels of education. Predictive models are used "to inform education policy in its data collection and use, these measures, in conjunction with other indicators of student achievement, can help educators and legislators fine-

tune relevant policy instruments so that the ultimate goal of student proficiency can be realistically attained by all students" (Mohammed, 2008, p. 184).

A predictive model extracts useful data into information that is comprehensible by discovering patterns that lead school officials to areas of need for student academic success and estimates what may happen in the future. The ability to predict future student academic success and the use of data to guide and monitor student growth is very powerful. Predictive models guide educational administrators in identifying and helping students succeed in meeting and exceeding federal and state accountability standards, all of which serve to monitor student performance. Yet, many schools are unable to meet Adequate Yearly Progress (AYP) due to the lack of progress and performance monitoring. By using predictive models to monitor student progress and performance, "Adequate Yearly Progress targets would be more realistic, and schools and their stakeholders would realize continuous improvement if incremental increases in expected growth were monitored and maintained" (Mohammed, 2008, p. 177).

Predictive models with the ability to track at-risk indicators are crucial in the development and maintenance of student academic success. Following data that is recorded to track student progress and performance is crucial to ensuring student academic success and achievement. Understanding this concept will help administrators and teachers in identifying predictive models and their use for abstracting crucial information. "Many systems of predictive modeling have been developed based on administrative data. The evolution of these systems, strangely enough, began with computation of the average, as it was a major force in creating the interest and incentives to develop better predictive models" (Steen, 1994, p. 1836).

2.3 Components of Predicting

It is no secret that school districts are defined by their accountability rating. Campuses are also under the same scrutiny of maintaining academic excellence. Performance, curriculum, and progress monitoring help administrators and teachers develop tools to predict student academic success. Developing a predictive model and identifying the many components that must be acknowledged in the development of a predictive model serves the purpose of reaching goal attainment. Data accumulation is easy to retrieve and readily available to school districts. School districts have multitudes of information on student demographics, assessments, and other pertinent information. The greatest difficulty in understanding the components of a predictive model is identifying what variables are the most important in predicting student academic success. “Whether predicting educational outcomes of student risk factors or identifying patient risk factors within the healthcare industry, both are comparable” (Steen, 1994, p. 1838).

Research incorporating a predictive model that reviews the progress, performance, and curriculum-based monitoring, and how such responds to intervention specializing in elementary level student educational success is a sought after phenomena. For example, components of prediction in the healthcare industry can be comparable to the educational setting to improve the identification processes of tracking student academic achievement. Identified are three historical approaches of prediction model development: “(1) selection and weighting of risk factors by expert opinion, (2) univariate analyses, and (3) multivariate analyses. Future prediction models will be based on neural network techniques or cluster analysis, as these prediction models have evolved, there has been a steady increase in their predictive power” (Steen, 1994, p.1836). The sole basis of using expert opinion cannot be the factor for determining risk factors. Collected data must be analyzed using a predictive model to gain a more accurate projection of the at-risk

possibilities. “The expert opinion approach has too many weaknesses to be more than a starting point until enough data are collected to allow the next phase of modeling to commence” (Steen, 1994, p. 1838).

Components that lead administrators and teachers in determining if students are at-risk of failure are explained in greater detail in section 2.3.A below. Explanation and identification of at-risk students is necessary to understand why a predictive model must be used to track performance and progress. Another component in the predictive modeling process is to not only identify and track at-risk students, but students that are on target, as well as how administrators and teachers are able to guide those students in achieving commended academic performance. Examining CPAD as a predictive modeling tool through a logic model methodology that predicts student success at the elementary school level will be analyzed in the methods section of this study. Further analysis from local district, AEIS, and AYP reports will be determined through methods explained in detail in this chapter.

2.3.A At-Risk Student Components

High stakes testing is not something that administrators and teachers will be able to forgo by placing it on the back burner of educational considerations. High stakes testing must be at the forefront of every administrator and teacher’s mind. Sub-group populations are the groups that are identified in both state and federal accountability measures. Utilizing a database that easily recognizes and identifies students from sub-groups and those students that reach beyond just one tracked sub-group, is crucial in the accountability rating process. “The passage of No Child Left Behind (U.S. Department of Education, 2001) placed schools under pressure to achieve standards and improve the proficiency of all students, including those who were English

Language Learners (ELL), received special education services, from ethnic minority backgrounds, or economically disadvantages" (Deno, et al., 2009, p. 44).

Students in elementary school can be potential at-risk candidates. Administrators and teachers at the elementary school level are the key to identifying these students early and placing them on track to becoming productive and successful as middle and high school students. Elementary level education is in preparation of middle school, however at the elementary level, students are catered to, and teachers are held responsible for student success rather than the opposite at middle and high school levels where the students are responsible for student learning (Eisner, 2011). At-risk students do not become at-risk starting at the middle school level or at the high school level. Indicators such as failure to be promoted, excessive absenteeism, disengagement, low performance, abused and neglected students, behavior issues, and mobility are all key factors that affect elementary school students as well as middle and high school students (Iver, 2010; Swanson, 2004; Rima-Shore, 2009). At the elementary school level, administrators and teachers ensure that students have the foundational skills to be successful in middle and high schools. Elementary administrators and teachers can determine interventions, strategies, and special services to help students succeed throughout their educational careers.

In Texas, 13 indicators are used to identify at-risk students (Agency, T. E. A, 2011). These indicators are identified and tracked within the Public Education Information Management System (PEIMS) and are subsequently listed. The student:

1. is in prekindergarten, kindergarten, or grade 1, 2, or 3 and did not perform satisfactorily on a readiness test or assessment instrument administered during the current school year;

2. is in grade 7, 8, 9, 10, 11, or 12 and did not maintain an average equivalent to 70 on a scale of 100 in two or more subjects in the foundation curriculum during a semester in the preceding or current school year or is not maintaining such an average in two or more subjects in the foundation curriculum in the current semester;

3. was not advanced from one grade level to the next for one or more school years; (Note: From 2010-2011 forward, TEC 29.081 (d-1) excludes from this criteria prekindergarten or kindergarten students who were not advanced to the next grade level as a result of a documented request by the student's parent.)

4. did not perform satisfactorily on an assessment instrument administered to the student under TEC Subchapter B, Chapter 39, and who has not in the previous or current school year subsequently performed on that instrument or another appropriate instrument at a level equal to at least 110 percent of the level of satisfactory performance on that instrument;

5. is pregnant or is a parent;

6. has been placed in an alternative education program in accordance with TEC §37.006 during the preceding or current school year;

7. has been expelled in accordance with TEC §37.007 during the preceding or current school year;

8. is currently on parole, probation, deferred prosecution, or other conditional release;

9. was previously reported through the Public Education Information Management System (PEIMS) to have dropped out of school;

10. is a student of limited English proficiency, as defined by TEC §29.052;

11. is in the custody or care of the Department of Protective and Regulatory Services or has, during the current school year, been referred to the department by a school official, officer of the juvenile court, or law enforcement official;

12. is homeless, as defined NCLB, Title X, Part C, Section 725(2), the term “homeless children and youths”, and its subsequent amendments; or

13. resided in the preceding school year or resides in the current school year in a residential placement facility in the district, including a detention facility, substance abuse treatment facility, emergency shelter, psychiatric hospital, halfway house, or foster group home.

Identifying at-risk students is a major aspect of predicting student outcomes. However consistently monitoring students is equally important in the predictive model approach.

2.3.B Monitoring At-risk Students

The National High School Center (NHSC) (Monrad, 2007) has an approach to dropout prevention with administrators and teachers reviewing early warning signs as key indicators to help detect at-risk students before they drop out of high school. The NHSC suggests strategies be established and reviewed long before students enter high school. Predicting student progress and performance at the middle school level is crucial (Monrad, 2007). However, the area that has not been closely monitored or researched is the prediction of student progress and performance at the elementary school level.

Progress-based monitoring or curriculum-based measurement (CBM) is monitoring that identifies students progress and performance to ascertain students’ needs, and is a best practice in monitoring all students, whether they are special education or regular education. Constant monitoring and observations can lead to making better choices based on academic need. “CBM

provides schools with the ability to do more than monitor progress for students as part of response to intervention (RTI)" (Shinn, 2007, p. 609).

Monitoring at-risk students by utilizing variables to measure characteristics correlated with students who drop out of school to include socio-economic characteristics, school related behaviors, and psychological states are considered pieces of data elements that are used in most monitoring systems based on 23 variables that support personnel use in evaluating students (Webster, 1989). Although longitudinal analysis would be a best practice in identifying at-risk students and tracking these students throughout their entire academic careers, it is ultimately a difficult task due to the logistical inability to consistently track students throughout their entire education. Therefore, the state of Texas, for example, provides school districts with the list of 13 at-risk indicators. "School districts are able to identify areas of program strengths and weaknesses so that where necessary, structural change and changes in curriculum and methods of delivery will be made" (Webster, 1989, p. 8). "Although definitions of at-risk children vary, there are recurrent themes in the definitions that represent a general consensus. First, at-risk students are students who, for whatever reason, are at-risk of not achieving the goals of education, of not meeting local and state standards of high school graduation, and of not acquiring the knowledge, skills, and dispositions to become productive members of society, Second, at-risk students are the children who exhibit behaviors that interfere with attaining an education. Finally, at-risk students are those whose family background characteristics may place them at-risk" (Vitale, 1994, p. 325).

2.3 C Identifying at-risk in elementary level

The classroom teacher usually assesses the identification of at-risk students at the elementary school level. Many conversations concerning behavior, student work portfolio,

learning incapacities, discipline, and parental engagement all serve as factors in determining if students are subject to becoming at-risk. “Teacher prediction of student achievement begins early in kindergarten when classroom teachers assess readiness for reading and make recommendations for reading group placements in first grade. The earlier teachers can identify at-risk students, the earlier intervention may begin and the greater the likelihood of positive effects” (Gaines & Davis, 1990, p. 4).

2.3.D Early Childhood Assessment

Early childhood assessment is used for various reasons, and among these reasons is the identification of at-risk students at an early age. Among all the dimensions that are used to create early childhood assessments in Texas to meet federal accountability, the assessment of evaluated choice and recognition for this study’s purpose is the Texas Projected Reading Inventory (TPRI). This early childhood assessment instrument is used to predict students’ academic success, based on observed evaluations, teacher assessment in phonics, comprehension, and fluency. The TPRI helps administrators and teachers determine if a student is on reading level for their grade level. For school districts to effectively monitor student progress, it is imperative to continuously monitor performance, curriculum, and progress monitoring. ‘“First, they are all criterion referenced and share properties related to assessments that can be identified as curriculum based. Rous (2007) examined information from Salvia and Ysseldyke (2007), who defined curriculum-based tools as "assessment methodologies that are used to collect and evaluate student achievement data in order to monitor student progress” (p. 24).

In early childhood education, the teacher is the first responder to a student that is in need of intervention. “The assessment process inspires speculation about potential changes to the

preschool environment, which is something that is under the control of teachers. Psychometric data, on the other hand, typically inspires speculation about innate differences and the adequacy or inadequacy of home environments neither of which is under the control of teachers. Teachers recognized that these data could serve as a benchmark for exploring skills development of children in future years. Unlike normative data gathered on national samples, this kind of data is clearly representative of the population served by this agency and therefore, represent a valid point of comparison for future samples" (Strand, 2007, p. 213).

2.3.E TAKS (Texas Assessment of Knowledge and Skills)

The Texas Assessment of Knowledge and Skills (TAKS), as a testing and accountability instrument, was brought to the forefront in 2003. There were several assessments prior to TAKS, such as Texas Educational Assessment of Minimum Skills (TEAMS) and Texas Assessment of Academic Skills (TAAS). The new assessment implemented in the 2012 school year is the State of Texas Assessment of Academic Readiness (STAAR). Names may change; however, the process of assessing student performance is never-ending and is what drives state and federal accountability standards. Although there is controversy about using assessments to determine at-risk students, it is nonetheless the accountability assessment in the state of Texas, and the one school districts must meet in terms of minimum standards to remain in academic compliance. Students that fail to meet the minimum standards of the TAKS assessment are determined to be at-risk.

According to the 2010, Annual Report of Texas Public Schools, the understanding of TAKS results by definition and method follow three categories for performance:

1. Commended performance. This category indicates high academic achievement. Students in this category performed at a level that was considerably above the state passing standard.
2. Met the standard. This category indicates satisfactory academic achievement. Students in this category performed at a level that was at, or somewhat above, the state passing standard.
3. Did not meet the standard. This category indicates unsatisfactory academic achievement. Students in this category performed at a level that was below the state passing standard (Austin, T., 2010, p. 26).

2.3F Limited English Proficient (LEP)

According to federal law, No Child Left Behind Act of 2001 and Title IX, the following criteria define students that are Limited English Proficient (LEP), and automatically label a student as at-risk.

The term limited English proficient, when used with respect to an individual, means an individual:

A. Who is aged 3 through 21;

B. Who is enrolled or preparing to enroll in an elementary school or secondary school;

C. Who was not born in the United States or whose native language is a language other than English:

    a. who is a Native American or Alaska Native, or a native resident of the outlying areas; and who comes from an environment where a language other than English has had a significant impact on the individual's level of English language proficiency;

b. who is migratory, whose native language is a language other than English, and who comes from an environment where a language other than English is dominant;

D. Whose difficulties in speaking, reading, writing, or understanding the English language may be sufficient to deny the individual

a. the ability to met the stat's proficient level of achievement on state assessments described in section 111(b)(3);

b. the ability to successfully achieve in classrooms where the language of instruction is English; or

c. the opportunity to participate fully in society.

2.3G Special Education (SPED)

The definition of special education according to federal law as established in The Individuals with Disabilities Education Act (1975) is specially designed instruction that is provided at no cost to meet the needs of a child with a disability. Special education includes instruction conducted in the classroom, in the home, in hospitals and institutions and in other settings.

2.3.H Mobility

Mobility among students is not a term that is identified as automatically labeling students as at-risk; however, there are relatable factors, which suggest that high mobility rates do have an effect on a student's academic success. The higher the mobility rates of students the more likely chance that students experience academic gaps (Engen, 2006). Engen, in the *Journal of Educational Research* reviewed a quantitative study conducted by Isernhagen and Bulkin (2011) for the National Dropout Prevention Center, and reported: "high mobility students in Nebraska

demonstrated a persistent pattern of lower achievement scores on criterion-referenced assessments versus their non-highly mobile classmates. These findings corresponded to research conclusions that mobility is associated with lower achievement" (Engen, 2006, p. 18). Thus, students that are highly mobile, such as students whose parent is in the military, may be identified as being at-risk of failure in shcool. "Students who moved often scored lower on tests than did their peers, although mobility was only one influence among other significant factors, such as race, income, and grade level"(Engen, 2006, p. 18). Military students can have a high mobility rate due to parental deployments and other military-related considerations such as family moves from one military installation to another.

2.3.I Military

Children of military families face many challenges. From separation anxiety, to the stress of a loved one not being at home in a consistent manner and, to the fear of knowing the possible dangers that they are exposed to. Each challenge, singularly or combined, automatically places a student of a military parent in difficult circumstances when it comes to academic success and achievement at school. Canon (2011) reviewed information from the Research And Development (RAND) non-profit organization, Center for Military Health and Policy Research, and found that "long and frequent deployments, with short dwell times in between, have placed stresses on army children and families already challenged by frequent moves and parental absences. These stresses may be present in the form of social, emotional, or behavioral problems among children at home and at school" (Canon, 2011, p. 1). According to information reviewed Canon, and reported by (RAND), "military students do not meet the criteria of Texas at-risk indicators (Canon, 2011, p. 1) to be categorized as at-risk. "According to the study, the longer parental deployments were, the larger the impact on child academic achievement. Children who

participated in the study were found to have lower achievement scores when their parents had deployed 19 months or more since 2001, across all academic subjects" (Canon, 2011, p. 1). Monitoring student academic success in small progressive growth achievement practices through assessment instruments help administrators and teachers predict if at-risk students are progressing along on an affirmative course.

2.3.J Using Value-Added Growth To Monitor Student Academic Achievement

When creating a predictive model, monitoring progress and value added growth to student academic performance between assessments from assessed data provide useful information to administrators and teachers. Jenkins, Graff, and Miglioretti (2009) conducted research that analyzed special education and how to of use progress monitoring. Progress monitoring is not only good to use for special need students, but for all students in general when tracking progress and determining value added between assessments. Jenkins, Graff, and Miglioretti (2009) found that it was possible to attain the same validity of growth whether assessments were given more or less frequently. "Our results suggest that progress monitoring can be scheduled in more efficient ways without detracting from the validity of the assessment results" (p. 161). Thus, affording administrators and teachers the opportunity to respond to student needs in an aggressive manner is essential in fitting the intervention to student academic need.

2.3.K Response To Intervention (RTI)

Immediate evaluation through the monitoring of progress, curriculum, and performance to identify at-risk students is crucial to creating a predictive modeling tool that provides early warning notification. According to the Texas Education Agency's report "TEA: Special Education in Texas 2006," identifying student's needs in an immediate response is more

probable in helping at-risk students achieve academic success. Monitoring progress and performance opens doors to interventions that are needed to help fill academic gaps. Intense intervention is a concept and practice that is critical to identifying students that are in need. Utilizing and incorporating the components of the Response to Intervention (RTI) model "is expected to have a positive effect on schools across the state. RTI may be described as a model addressing the needs of all students through a continuum of services which provide: (1) high-quality instruction (2) frequent monitoring of student progress; (3) data-based school improvement; and (4) the application of student response data to important educational decisions" according to Texas Education Agency Division of Special Education in Texas (Coordination, 2006, p. 1).

Predicting what interventions students need is frequently based on the results of the assessments administered. Immediately students can be placed on intervention plans. "Progress monitoring is a critical component to the RTI model because it provides immediate feedback as to how well the student is responding to the teaching. With timely feedback, the teacher has the opportunity to change direction or increase the intensity of instruction" (Moore & Whitfield, 2009, p. 623).

Administrators and teachers who are not familiar with understanding how to use data to drive instructional decisions, can be intimidated. They may find the data-based decision-making process to be an overwhelming task. However, data is the pure source in how administrators and teachers can better pinpoint areas to be targeted for growth, as well as what needs to be re-taught or re-visited within the curriculum. Data helps teachers in better serving students. "No standard protocol has been mandated for directing the RTI process, however, that progress monitoring data are used for decision making purposes. Data aid teachers in making judgments to determine

when additional support is needed, or conversely, when such intensive instruction no longer is needed because a student has responded well to intervention" (Stecker, 2007, p.50).

According to Betts (2008) "Intervening earlier, perhaps in middle school or even in the later grades of elementary school, could perhaps increase the effectiveness of the dollars spent on intervention" (p. 52). Interventions for at-risk students are crucial. However, monitoring students that are academically successful and have opportunities to progress to commended academic performance is equally crucial.

2.3.L On Target Students

"On-Target" students are defined as meeting academic expectations (Texas, Texas Education Agency Definition of Terms, 2011). Academic focus is frequently on at-risk students. However, when guiding "target" students to success, administrators and teachers may think that students that are doing well academically (those students meeting minimum standardized assessment criteria) and thus, are not in need of interventions. On the contrary, "target" students should be monitored just as frequently as at-risk students because, in the state of Texas for example, reaching commended performance is the pinnacle "rating" and reveals students are ready for college preparation. "Our goal as a campus as it relates to assessment in all areas tested is not only to meet the standards, but also increase the number of students that perform at the commended level each year. If students are scoring at the commended level, they are more likely to be successful in college" according to the Department of Education Data Express Definition of Terms (Education, 2011, p.11TX3). Using predictive modeling by monitoring students that are meeting minimum standards, ultimately will afford them educational opportunities to be successful lifelong learners.

2.3.M Monitoring

Students monitored in both progress and performance measured assessments will undoubtedly have an area of need to be addressed. Enrichment activities help students meet and exceed their academic potential. Students that need extra support and have been clearly identified as needing intense intervention may think that the extra help and work is difficult and therefore may lack motivation to be successfully engaged. However, when identified and placed under intense intervention, students can improve in addressed areas, and student motivation will increase, as will student comprehension. "These measures are important because they possess several desirable features typical of progress-monitoring tools, which have been shown to be strong predictors of motivated and self-regulatory behaviors, and possess many advantages relative to more global self-report scales of motivation" (Cleary, 2009, p. 154). Academically successful students benefit from predictive modeling and monitoring.

2.3.N Commended Performance

Administrators and teachers recognize that meeting minimum standards are unacceptable, especially when students can attain higher and more rigorous levels of achievement. If a student is measuring at the minimum standards level, then it is an administrator and teacher's duty to ensure that the student reaches higher levels of potential such as commended performance. Whatever the assessment, from reading to math to science, or any other content area, it must be expected that students reach their highest academic potential and therefore, need to be continuously pushed to obtain mastery levels.

"The TAKS program includes a formal performance category for students who demonstrate high academic achievement considerably above the passing standard. Standards for commended performance were established in 2003 without a phase-in" (Agency, T. E. A., 2010,

p. vi). "To achieve state exceptional recognition through the Blue Ribbon Program campuses are eligible for consideration for high academic achievement where the Met Standard percentage for each TAKS tested grade level is in the 90th percentile (top 10%) of the state…" (Agency, T. E. A,, 2010, p. 4). Students that score commended performance are predicted to be college ready. Students that possess the academic potential of becoming commended performers must be monitored through performance, curriculum, and progress. Using predictive modeling to observe student academic achievement in performance, curriculum, and progress monitoring, will benefit administrators and teachers in predicting student academic success.

2.4 Predictive Models

It is difficult to keep track of so many points of data without a database. Schools interested in using available data for optimal impact need an electronic data system that includes individual student-level data that can track students over time and also allow risk factors to be assessed (Jerald, 2006). Many other factors are predictive and available in data and it is the combination and level of such factors, which make one student more likely to drop out than another. Because dropping out of school is a slow process of disengagement for most students, tools, which give administrators and teachers an opportunity to identify and address early indicators signaling the need for more support for students to stay in school, are vital, according to Adaptive Technologies Report "Using Predictive Modeling to Improve High School Dropout Prevention" (Technologies, 2008).

There are many progress monitoring tools used in predictive analytics to create statistical models of future behavior. Predictive analytics is the area of data mining concerned with forecasting probabilities and trends. Each predictive model is a technological tool that searches for predefined variables of interest to identify specific interventions. Building a predictive model

is vital to acquiring the data and information needed to assist administrators and teachers in identifying, predicting, and maintaining students' academic success.

A predictive model is made up of a number of variable factors that are likely to influence future behavior or results. In marketing, for example, a customer's gender, age, and purchase history might predict the likelihood of a future sale. There exists a need for strategic, predictable, and analytical data collection and processing methodologies, which afford administrators and teachers the opportunity to "get ahead of the issue and stay there" (Technologies, 2008) for the sake of potential student dropouts. The No Child Left Behind Act (NCLB), as well as any other legislative education initiative, cannot and will not solve the problem by merely raising the bar and demanding more from students. All too often, educators fail their students by not striving to develop and implement better methodologies for addressing the issue of school dropouts (Technologies, 2008).

Predictive models help collect and adapt problems toward individual students in order to achieve an engaging learning environment with them. This should not only help lagging students catch up to the standard, but also bring them back into the learning sphere (Woolf, 2010).

Early warning systems provide information about those students who are displaying risk factors which predict an increased likelihood of dropping out of high school. Once identified, students can be connected to dropout prevention interventions and monitored throughout the school year. Ideally, an early warning system allows users to identify students with accuracy, and further provides support to students through interventions. The results: improved graduation outcomes and increased academic success for students (Therriault, 2008).

2.4.A Database

The first, most important step in building a database is to know what the user needs. Determining what information is desired in the database so that the database being built will meet the needs of the school district is key, most notably as it relates to determining student academic success. Although databases are quite flexible and can be adjusted as needs change, it helps to have a general goal in mind. Data modeling is usually the next step in building the database. Deciding how to set up the data tables and establishing relationships with one another is imperative.

Foegen (2007) describes an assessment measure that determines levels of detecting student growth, when using a database to predict student academic outcomes. The description of the assessment measure that Foegen (2007) describes can be compared to the TAKS assessment in the state of Texas. Using the database and maintaining accuracy with data, as well as inputting said data into the database helps maintain student progress relative in their academic performance. "The most well established measures at the elementary level are the MBSP (Monitoring Basic Skills Progress) measures. These measures have empirical data supporting their reliability, criterion validity, and sensitivity in detecting student growth" (Foegen & Jiban, 2007, p. 132). Administrators and teachers must be responsive to all student data; this will be the most beneficial aspect of extracting predictive data from a predictive modeling tool. The purpose of creating a predictive modeling tool is crucial, and it must extract appropriate data to identify at-risk indicators of students being assessed.

2.4.B Building a Predictive Model

When building an appropriate predictive model, each indicator must be determined to serve as a predictor in the database. In order to build and maintain prediction models,

educational administration can utilize differing indicators. The most difficult aspect of building a predictive model can stem from a lack of integration between the database being mined, as well as the software tools being used to build the predictive models. Predictive modeling is a rigorous approach, which utilizes existing patterns of current data to statistically predict the behavior of at-risk students. A good layout in developing a plan to build a predictive model is to decide upon the target variable of what is to be predicted, i.e., student academic achievement. Using data that contains useful information, such as student demographics, including federal, state, and local at risk indicators greatly benefits a schools' ability to enrich the learning of students, especially if all of the data is compiled into a single database.

2.4.C Model Appearance

The predictive model appearance needs to be easy to read and user-friendly to manipulate. That is the entire premise of creating or discovering a predictive model that will do the job, a job that educational administrators and teachers need the model to do. Functionality is of importance, but to gain buy-in for the model, it needs to have the ability to produce specific reports based on specific data from the individual campus and student assessment results.

2.4.D Background on Models/Databases Reviewed

The standardized At-Risk indicators that the predictive models reviewed, for this study's purpose, include local, state, and federal standards that provide for 24 different variables which identify reasons for students dropping out of school. It is therefore important when creating a database to take each variable into account. This will provide the greatest amount of information to which a solution can then be applied. Of these 24 different variables, and in review of the most utilized predictive model databases in the United States, the following results are listed for each listed database. Dynamic Indicators of Basic Early Literacy Skills (DIBELS) only looks at

three indicators, Early Warning Data System (EWDS) examines twelve, LONESTAR ten, National Education Data Model (NEDM) eight, Southwest Educational Development Laboratory (SEDL) five, Research Brief Education (RAND) six, and Statewide Longitudinal Data Systems (SLDS) examines seven. CPAD includes eighteen of the indicators. Clearly, CPAD is a step above the others as it includes more possibilities for assessment and analysis, which then allows for more solutions, and earlier detections. CPAD in comparison to the other predictive models previously reviewed, serves to facilitate and guide administrators and teachers to customize individual campus needs. Therefore, this study has produced an in-depth examination and evaluation of CPAD.

2.5 Comprehensive, Powerful, Academic Data (CPAD)

Marie Yarberry, a former educator in Shining Star Independent School District, created CPAD. CPAD was designed to monitor student progress and performance at the elementary school level. The intention of utilizing this particular database was to identify students in need of interventions essential to becoming successful academically and to achieving mastery levels on standardized state assessments.

2.5.A Database Data Entry

CPAD stores data of at-risk indicator categories, demographics, and historical data for all students at the elementary school level. The database utilizes the application Microsoft Excel to filter information viewed on reports needed by administrators and teachers to identify at-risk indicators of students or sub-group populations. The database is a resource that can be easily manipulated through inputted data. CPAD permits administrators and teachers to enter at-risk indicator criteria for each student into the software application. Moreover, any new indicators can be added or removed on an “as needed”.

2.5.B Accountability

CPAD incorporates how state and federal accountability agencies monitor student academic performance, and thus, communicates such to administrators and teachers. State and federal accountability agencies monitor how students are performing by race, limited English proficiency (LEP), economically disadvantaged, and other sub-group criteria for all subject areas. The identification and monitoring of each individual student, as well as sub group population criteria, is advantageous to administrators and teachers facilitating student academic progress to meet federal and state accountability expectations.

2.5.C Monitoring

Incorporating CPAD can better direct implemented instruction monitored by administrators and teachers to facilitate the progress of students in their efforts to reach their full potential. CPAD assists administration and teachers with monitoring student performance and progress from predictive data demonstrating growth and value added through data obtained from weekly common assessments, district benchmarks, and periodic diagnostic testing in all administered subject content areas. "The purpose of progress monitoring is to represent student growth in the curriculum across the year; perhaps under varying instructional conditions" (Stecker, Lembke, & Foegen, 2008, p. 51). CPAD has been designed to assist administrators and teachers monitor student progress. "Monitoring progress, which typically begins by estimating a student's baseline performance, serves as the platform for setting annual growth goals and measuring subsequent growth" (Jenkins, Graff, & Miglioretti, 2009, p. 151). CPAD is developed to establish a baseline for students, TAKS assessment results. An established baseline implemented by Marie Yarberry, and used on student data, incorporated from each common assessment, mock/diagnostic assessment, and historical state standardized assessment followed

predictive percentages of student academic progress: 45%-1st attempt, 55%-2nd attempt, 70<-3rd on trials administered in October, late December, and early February, respectively.

CPAD incorporates data from state and local resources from one school year to the next. Predictive data is generated for administrators and students to identify student value-added growth from one assessment to the next. The continual progress monitoring of students' academic achievement relative to performance indications from weekly common assessments to mock/diagnostic testing to state standardized assessment data is crucial for administrators and teachers. This process ensures academic success, as students understand what they have learned from the week's lesson and objective. Additionally, the process ensures that teacher instruction and student learning follows state mandated standards.

CPAD is designed to track student performance and also identify which students have made gains. CPAD is to provide information about those students who are not attaining benchmark standards or who may be at-risk of failing.

2.5.D Reporting

CPAD distributes the information necessary in identifying student information that aids administrators and teachers in their instructional decisions as aligned with student needs. Foegen (2007) states that using a database will create a flexible system that can monitor multiple grade levels. CPAD stores all demographic and academic data and predicts student performance and progress by assessing data from local and state assessments.

CPAD is a tool designed to identify historical student data and predict student academic progress and value-added between administered assessments throughout the elementary school year. CPAD is a tool designed to identify At-Risk students and prescribe appropriate interventions as needed. CPAD is a tool developed to aid administrators and teachers as they

identify what the student may need as related to intervention initiatives (Response to Intervention [RTI]), “because the progress-monitoring component of RTI should employ tools that are scientifically based” (Shinn, 2007, p. 601).

2.5.E Response to Intervention (RTI)

CPAD is designed as a tool for both special and regular education students. Additionally, CPAD was developed as a tool to identify students relative to where they have been and to signifying what progress and value has been added relative to student academic success. CPAD is a designed tool to assist administrators and teachers in the first critical steps of identifying that certain student may need RTI. “RTI has led to changes in decision making and instructional delivery for all students. One of the foundational elements of RTI is a technically adequate system of screening and progress monitoring” (Fuchs, Mock, Morgan, & Young, 2003 as cited in (Deno, et al., 2009, p.311).

2.5.F Predictive Outcomes

CPAD was developed to reveal student value-added growth from one assessment to the next. The continual progress of students understanding and performing on common assessments data is crucial for teachers to determine if students understand what they have learned.

CPAD is designed to aid administrators and teachers in determining if students are obtaining and maintaining the correct academic intervention, through the monitoring processes. As the academic successes increase, through the intervention process, so does the intervention change with the student’s level of ability. Interventions are fluid for each student as the student successfully meets specified academic achievement criteria. The intervention is always geared to the individual student. CPAD was developed to aid administrators and teachers as they identify areas of student academic weaknesses and areas to target for instructional growth.

2.5.G Future Research

CPAD was also designed to assist administrators and teachers when tracking the progress and performance of each student.

Students that are not meeting the criteria that administration has identified are subjected to the next level in the analysis of each item not correct in the assessment process. It is from the item analysis, as related to particular standardized released assessments, that administrators and teachers are able to pinpoint what essential knowledge and skills, objective and, student expectation are critical for each student relative to undergo intense intervention. The intervention can be from their homeroom teacher, from another teacher, instructional coach, and/or tutor. “Reconfiguring school resources to assist students at different levels of instructional intensity establishes a system of educational service for all students in need before they experience a lengthy cycle of failure. Early intervening services may ultimately reduce the number of students referred for special education or may reduce the impact of a disability on students academic progress. Emphasizing the use of evidence-based practices at all instructional levels contribute to student success and may eliminate or reduce ineffective instruction as a cause of poor student performance” (Foegen, 2008, p. 55).

CPAD was developed for any test in any state. Understanding and truly monitoring instructional strategies must be understood as the end result, and must be at the beginning of the development stage to fully incorporate the database. The reasoning for CPAD is the continuous process of monitoring student progress. Administration can monitor teachers and ensure that teachers are monitoring student’s progress. The entire premise of the database is to ensure that students are reaching their full potential of understanding and grasping the curriculum. For

students to be successful on any state assessment, they must continuously be assessed and monitored at the local level.

CPAD was formulated to calculate the predictive progress and performance on student's academic success. Refer to the logic model incorporated in Appendix 3-9 as to how CPAD has been designed to assist elementary administrators and teachers.

2.6 Logic Models

A logic model is a planning tool that assists individuals who want to determine if a program is beneficial. Many components are incorporated within a logic model. However, those components are an exact diagram of what the program is intended to accomplish. "The model describes logical linkages among program resources, activities, outputs, audiences, and short, intermediate, and long-term outcomes related to a specific problem or situation. Once a program has been described in terms of the logic model, critical measures of performance can be identified" (McLaughlin, 1999, p. 65). There are many ways to develop a logic model, and the differences are not necessarily a major concern. The establishment of the logic model is visual, and can be transformed into a comprehensible tool that details the flow of the planning process of a program being examined. Planning is key in developing a logic model. "The application of the logic model as a planning tool allows precise communication about the purposes of a project, the components of a project, and the sequence of activities and accomplishments. Further, a project originally designed with assessment in mind is much more likely to yield beneficial data, should evaluation be desired" (McCawley, 2012, p.1).

2.7 Summary/Conclusions

Chapter Two affords the reader the opportunity to gain background knowledge on predictive modeling tools, which are supportive in student academic achievement, as well as key

elements and components that surround CPAD and the accountability measures from both state and federal standards. The importance of monitoring student academic success through the means of a predictive modeling tool is crucial to ensuring student progress and provides for a prompt response to intervention.

Finally, a logic model has been created to illustrate the processes, outputs, and outcomes of CPAD. The logic model provides a systematic, visual method to best present a planned program as such relates to underlying assumptions and the theoretical framework.

CPAD, as examined in Chapter Two, is described and communicated through the lens of the practitioner. Details of the predictive monitoring process, identification of students at-risk, and response to intervention, are explained as well in detail and illustrated in a logic model methodology in Chapter Two.

Chapter 3: Methodology

3.1 Introduction

The purpose of this study is to determine if the CPAD database organization and processes are most effective in predicting student academic achievement, to assist school administrators and teachers in identifying students at-risk of achieving minimum standards through an analysis of three years of accumulated student assessment data.

3.2 Quantitative Analysis

The rationale for using quantitative research methodology relates to Krathwohl (1988) who contends the uniqueness of the approach to be studied and its potential advantages over present methods can have important consequences and should be pointed out. Furthermore, Glass, McGaw, and Smith (1981) suggest evidence based solely on singular published research tends to be biased toward positive results. However, meta-analytic studies will reveal where findings are relatively strong and where more research is needed. Therefore, a quantitative analysis of academic achievement, especially in terms of TAKS results could very well provide a magnitude of evidence revealing the significance of the predictive modeling tool.

Gay (1992) states "the experimental method is the only method of research that can truly test hypotheses concerning cause-and-effect relationships. It represents the most valid approach to the solution of educational problems, both practical and theoretical, and to the advancement of education as a science" (p. 298). The experimental method, according to Gay, is both the most demanding and the most productive method of research and when well conducted, "experimental studies produce the soundest evidence concerning hypothesized cause-effect relationships" (p. 298).

In order to consider the efforts, a 2 x 3 repeated measures multivariate ANOVA statistical analysis was conducted for each area assessed (Reading and Math).

ANOVA repeated measure designs are analyzed with a repeated-measures analysis of variance. This methodological approach better ensures that the same participants are being measured repeatedly. This type of design and analysis is also called a within-subjects design and within-subjects analysis of variance because the comparison is within, not between, the different participants or subjects (Mertler & Vannatta, 2005). The purpose of an ANOVA is to test whether the means for two or more groups are taken from the same sampling distribution. The multivariate equivalent of the test is the Hotelling's T. The Hotelling's T tests whether the two vectors of means for the two groups are sampled from the same sampling distribution (Morgan, Leech, Gloeckner, & Barrett, 2004, p. 1). Repeated measures ANOVA tests the equality of means. However, repeated measures ANOVA is used when all members of a random sample are measured under a number of different conditions (UCLA, 2013, p. 1). As the sample is exposed to each condition in turn, the measurement of the dependent variable is repeated.

The validity of the statistical analysis ANOVA, according to (Mertler & Vannatta, 2005), is completed with-when the between-groups variability is measured. Such is actually measuring differences due to the effect of the treatment, or to chance. In contrast, the within-groups variability is caused only by chance differences. Within each treatment or group, all subjects in that sample have been exposed to the same treatment or share the same characteristic. The researcher has not created affects that would result in different scores. Obviously, individuals within the same group will likely have different scores, but the reader will realize that these differences are due to random effects (Mertler & Vannatta, 2005).

3.3 Participants and Sample

Administrators and teachers within the Shining Star Independent School District (SSISD) from the participants campuses provide enlightening information relative to which predictive modeling tool best suits their schools.

The sites researched within the study were elementary campuses in Shining Star Independent School District that implemented the CPAD during the timeline associated with this study. Marie Yarberry assisted administrators and teachers in the implementation, utilization, and staff development of the CPAD.

3.3.A Treatment Group Elementary School AEIS Background

This portion of information reflected in Table 1 shows the percentages of ethnic diversity of students from the elementary school treatment group, and the years they were enrolled during the CPAD implementation. This information includes student percentages relative to the campus.

Table 1 Treatment Group Ethnic Diversity

TAKS years	At-Risk	Hispanic	White	African American	Economically Disadvantaged
2007-2008	75.9%	94.5%	2.7%	2.3%	96.4%
2008-2009	73.3%	92.3%	3.8%	3.4%	93.3
2009-2010	63.8%	91.3%	5%	3%	96%

Table 2 reflects the 2007-2008 overall campus percentages in Grade 3 Reading 60% and Mathematics 72%. In comparison to the campus group and district, percentages for Reading were 80% and 84% respectively. In Mathematics, campus group and district percentages were 80% and 82% respectively. According to the Academic Excellence Indicator System (AEIS) during the school year 2007-2008 the accountability rating was Academically Acceptable.

Table 2 Treatment Group Percentages of Subjects Tested

	2007-2008	2008-2009(CPAD Implementation)	2009-2010
Reading	60%	77%	83%
Math	72%	88%	93%
Accountability Rating	Academically Acceptable	Recognized	Recognized

CPAD was implemented in the 2008-2009 school year. This information includes student percentages relative to campus group, district, and state. Campus percentages in Grade 4, Reading 77%, Mathematics 88%. In comparison to the campus group and district, percentages for Reading were 82% and 87% respectively. In Mathematics, campus group and district percentages were 87% and 90% respectively. According to the Academic Excellence Indicator System (AEIS) during the 2008-2009 school year, the accountability rating was Recognized.

The third column reflected in Table 2 reveal information for the 2009-2010 school year. This information includes student percentages relative to campus group, district, and state. Campus percentages in Grade 5 were Reading 80%, and Mathematics 89%. In comparison to the campus group and district, percentages for Reading were 79% and 88% respectively. In Mathematics, campus group and district percentages were 85% and 90% respectively. According to the Academic Excellence Indicator System (AEIS) during the school year 2009-2010 the accountability rating was Recognized.

Table 3 reflects the percentages of ethnic diversity of students from the elementary school comparable group, and the years they were enrolled. This information includes student percentages relative to the campus.

Table 3 Comparable Group School Demographics

TAKS years	At-Risk	Hispanic	White	African American	Economically Disadvantaged

2007-2008	76.3%	92%	3.5%	4.3%	96%
2008-2009	82.4%	93.3%	3.4%	2.9%	95.3%
2009-2010	73.7%	93.1%	3.5%	3.3%	93.2%

Table 4 reflects the 2008 overall campus percentages in Grade 3, Reading 54%, and Mathematics 63%. According to the Academic Excellence Indicator System (AEIS) report during the 2007-2008 school year the accountability rating was Academically Acceptable.

Table 4 Comparable Group Percentages of Subjects Tested

	2007-2008	2008-2009	2009-2010
Reading	54%	69%	82%
Math	63%	81%	83%
Accountability Rating	Academically Acceptable	Recognized	Recognized

3.4 Ethical Considerations

This researcher sought and was granted approval to conduct the study from the Institutional Review Board of the University of Texas at El Paso. The data used for the in-depth examination and evaluation of the CPAD database involved data from administrator and student data, therefore strict adherence to principles of ethical research was required. At no time did identifiable student or teacher data leave the school district used for this study. Additionally, no attempt was made to use student data at the level of individual teacher to identify, rank, or classify teachers based on their students' achievement. Student data was aggregated by lexile/quantile scores from state exams administered for three consecutive years for each sample set campus.

3.5 Quantitative Methodology

The overall methodology utilized for this study was designed as evaluation research where one of the main instruments of analysis was a logic model methodology to best conduct an in-depth examination and evaluation of the CPAD and its decision-making tools and processes. Logic models can be described as graphical depictions of the logical relationships between the resources, activities, outputs and outcomes of a program. There are many methods by which logic models can be presented. The underlying purpose of constructing a logic model is to assess the relationships between the elements of the program; if the resources are available for a program, then the activities can be implemented. If the activities are implemented successfully then certain outputs and outcomes can be expected. Logic models are most often used in the evaluation stage of a program, they can however be used during planning and implementation. By describing CPAD in this manner, the practitioner/researcher had a better method of defining and measuring CPAD's abilities. Performance measures can be drawn from any of the steps. However, for the purpose of this study, one of the key insights of the logic model is the importance of measuring outcomes. The measurement of the outcomes are performed through a quantitative analysis and reported in Chapter 4 of the study. The results of this provide insight as to how the outcomes relate to successful achievement of the mission or program goals of CPAD.

For this study, a quantitative methodology approach was preeminent in presenting the statistical data. The data is used to prove/test the qualities of CPAD as a predictive modeling tool as a means of aiding administrators and teachers in identifying at-risk student's academic achievement. Using a theory of action approach, the research issue will be analyzed through the quantitative methodology approach. Quantitiative analysis research, will be conducted utilizing a 2 x 3 repeated measures statistical test to help analyze the data. The approaches for testing data

will be a repeated measure using cross tabulation analyses, to compare each of the two sample sites, and a multi-faceted Analysis of Variance (ANOVA). The analysis will be using Statistical Packages for the Social Sciences (SPSS) software to report results.

3.6 Quantitative Technique for Data Analysis

For this study, the quantitative technique incorporated different statistical tests to produce the results. "Quantitative research designs are either descriptive (subjects usually measured once) or experimental (subjects measured before and after a treatment). A descriptive study establishes only associations between variables. An experiment establishes causality" (Hopkins, 2000). This study reviewed and determined student lexile/quantile score measures received on Texas Assessment of Knowledge and Skills (TAKS) over a three-year period. Each site studied, followed a set of students, the treatment group utilized strategies and procedures of CPAD and the comparable group did not. Each sample school followed the same students for three consecutive school years. The longitudinal analysis utilizing a repeated measures analysis statistical test procedure determined if there was a significant increase in lexile/quantile scores for each student and subject area over time. The Academic Excellence Indicator System (AEIS) report showed that both the studied schools had higher ratings, however the treatment group, when Marie Yarberry implemented the CPAD strategies and procedures, prove that student lexile/quantile scores had significant growth during the implementation of CPAD. The assumption is that CPAD and the implementation of associated strategies and procedures, such as professional learning communities, tutoring, mock testing, goal setting meetings, staff development and training will increase student academic achievement on state assessments.

3.7 Data Collection Strategies

The collection strategies utilized to gather student data was based on information collected from both sample sites. The two sample sites consisted of the treatment group that received the CPAD processes, and the comparable school, which did not. Each of the campuses reviewed student assessment data throughout the 2007-2008, 2008-2009, and 2009-2010 school years. The CPAD process and strategies were implemented during the 2008-2009 and 2009-2010 school years for the treatment group. The sample sets of the student data gathered was from the same cohort of students for each school year during the three years 2007-2008, 2008-2009, and 2009-2010. The individual student data was reviewed for the respective school years prior to, during, and after the implementation of CPAD. The sample was consistent throughout the identified elementary school years. The collected assessment data was analyzed using the student lexile/quantile scores from each students' reading and math state assessment results report retrieved from a Pearson Education database for the TAKS student assessment history report.

The data collection utilized was gathered from Shining Star Independent School District. A request to obtain approval to gather student data was approved after a meeting with the Shining Star ISD associate superintendent of research and evaluation. The specific request was to find a set of at least 30 students that were enrolled and were administered state assessments in each of the previously identified school years. These student scores from each sample site were placed within an excel spreadsheet. The data format obtained was student gender, student ethnicity, and at-risk indicators for each of the school years requested. Columns were added to the spreadsheet to obtain the student TAKS history report results for each assessment administered. The assessments of focus were reading and math, since both of these assessments

are administered in 3rd, 4th, 5th, grade levels. The student lexile/quantile scores for the respective school years were obtained and the values were entered into the excel spreadsheet. The excel spreadsheet was then merged with SPSS software to complete the analysis of the student data.

Data collection was based on state and federal accountability documents, and student data from each elementary school that incorporated the CPAD. Student data collected from each school also included a review of Academic Excellence Indicator System (AEIS) that provided reports on overall student performance for each assessment administered, total number of students within the grade level, percentages of students by ethnicity, economically disadvantaged, limited English proficient, at-risk, and mobility indicators. The AEIS reports reviewed included the school year prior to utilizing the CPAD procedures and strategies, the year during the implementation of CPAD, and the year after the implementation of CPAD.

3.8 Design and Plan of Analysis

In gathering the data from each sample site, a student TAKS assessment history report was examined for each individual student. This history report identified information from each assessment administered from grade 3 through high school. The report consisted of student demographical information such as PEIMS Identification (social security number), full name, date of birth, gender, ethnicity, economically disadvantaged coding, and school district local Identification. Identifying assessments taken over the course of each student's assessment history the collected data consisted of grade, language, test version, subject, test date, county/district/campus codes, score code, scale score, met standard rating, commended performance rating, and the test document number.

The researcher reviewed the TEA conversion charts which illuminated the horizontal/vertical scale scores, as well as the Lexile/Quantile measures. It became apparent that

the only means to compare apples to apples was to use a lexile measure for Reading and a quantile measure for Math. Thus a review of the school years researched (2007-2008, 2008-2009, and 2009-2010) incorporated a horizontal/vertical scale score as well as a lexile/quantile measure. The conversion charts examined were for each test type, grade level, subject area, and for each testing administration.

3.8.A Design

The study consisted of collecting information from the participants at three different moments in time: 1) before the treatment, 2) during the treatment, and 3) the year following the treatment. It was imperative that information using all materials be collected prior to the intervention since it would be impossible to ascertain if the groups under observation were initially different. Schools that participated in the study were assigned to one of two different groups, one being the experimental treatment group and the other being the control group. The treatment group received CPAD strategies and procedures, while the control group did not.

3.8.B A Priori Power Analysis and Statistical Significance

A prospective power analysis was conducted for this study. According to Stevens (2002), statistical methods for determining the appropriate sample size to achieve the desired power were followed: A sample size greater than or equal to 30 was needed in order to detect an effect size of .35 with a power = .8 (B = .2) using a statistical significance level of .05, assuming a moderate within factor correlation ($r = .5$) when there are three repeated measures (Stevens, 2002). No retrospective power (observed power in SPSS) analyses where conducted for any analysis in this study given that calculating power, given the effect size observed, was not useful and yielded no more information than observed p-values (Thomas, 1997). According to Thomas (1997), an observed effect size is dependent and inversely related to p-values and power. In

other words, statistical tests with high power will have low p-values and vice-versa. Therefore, using the observed variance and effect size to calculate power is just another way of repeating the statistical significance of the test (Thomas, 1997). With respect to the significance level used in this study, an alpha level of .01 was used for all repeated measures analyses performed.

3.9 Limitations of Study

The Shining Star Independent School District is located within a large urban area in the southwestern United States and serves approximately 65,000 students with 72% of those students identified as at-risk students. The demographics of the school district provided the backdrop for this study, but certainly were not within the control of the researcher.

The researcher's conscious and unconscious bias was an important limitation as related to this study. Objectivity is the ideal of research, especially research conducted at the dissertation stage. However, few individuals can completely achieve objectivity in research. The greatest limitation, even temptation, in this study was to develop a favorable attitude toward the CPAD database. Favorable feelings regarding CPAD were likely consequences and thus could contribute toward positive biases based on the researcher's past incorporation and utilization of the CPAD database. Additionally, the researcher had, previous to the study, developed a professional relationship with the designer and creator of the CPAD. Nevertheless, recognition of such biases constantly led the researcher to maintain essential objectivity during the course of the study.

To control for what Best and Kahn (2006) describe as *The Researcher's Unconscious Bias*, the researcher guarded against such a limitation and source of inherent error by initiating the following research steps:

1. Examined, for comparison purposes, other national and state databases to include:

- DIBELS, EWDS, CPAD, LONESTAR, DIBELS, NEDM, SEDL, RAND, SLDS; and

2. Employed statistical analyses, to include but not limited to a 2 x 3 repeated measures ANOVA, which were essential to ensuring study conclusions were valid.

Another limitation to this study related to a factor affecting the comparison across each researched school year. There was a noticeable amount of student information that was excluded. Examples of such excluded information was: Special Education student results, mobile students not included in this study, number of schools studied, the number of students studied, the number of years examined, the tests administered, and other factors pertaining to data collection such as Limited English Proficiency, and Socio-Economic status. Although the Shining Star Independent School District student population reflects a low socio-economic, bilingual population, the results of the study are limited to a cohort of third graders followed from 2007-2010. The generalization of the results was limited to this particular district and these particular students.

3.10 Delimitations of Study

The TAKS test measures mastery of grade level standards and is, by no means, the only way to measure student strengths and ability. This study was defined by the limits of the TAKS test. Lastly, the analysis of the impact of response to intervention for students identified as at-risk, by virtue of achievement rates, limited itself to the examination of children's weaknesses. In a world of diversity, and a future filled with even greater diversity, educators must be ever mindful of the strengths and gifts, which each child brings into the classroom daily.

3.11 Summary

Chapter Three begins with a description of the Shining Star Independent School District, which is a large district in the greater continental Southwest. A detailed account of how the research was conducted and the means of measuring such data was clearly identified. Students were identified and placed in meaningful and structured responses to intervention through the implementation of CPAD. This study was designed to bring to light the researcher's plan to study school district data regarding the impact of identifying students early and responding to CPAD interventions as a means of immediately improving academic achievement on assessments. The research design utilizing a theory of action, implementing a logic model, was presented as the appropriate tool for analyzing student-testing data over time. Limitations as well as delimitations of the study brought the chapter to closure.

Chapter 4: Data Analysis and Results

4.1 Introduction

Predictive modeling tools are designed to aid administrators and teachers in identifying at-risk students. Predicting student academic achievement is beneficial for the implementation of interventions. Administrators and teachers utilize best practices, and initiate interventions from day one based on information obtained from student academic achievement reports. Monitoring performance, curriculum, and progress aid in the compliance with state and federal guidelines. These processes, at different levels of education from elementary to college, utilize predictive modeling tools to determine areas of need that affect at-risk indicators.

Predictive modeling tools consist of many components presenting criteria to meet expectations in the identification of at-risk students. Consider an elementary campus that has been receiving disturbing signals based on results from state and federal performance standards after consecutive years of declining progress in terms of student pass rates on accountability assessments. Declinations and stagnate progress in passing rates for students in an elementary school for all tested subjects and appropriate grade levels must be a concern to administrators and teachers. Although administrators and teachers analyze data reports of performance, progress, and curriculum indicators of at-risk student criteria, students continue to struggle. Inabilities to achieve state and federal accountability standards from student assessment results at the elementary school level forces administrators and teachers to approach the data decision-making process with great care. The incorporation of an effective predictive modeling tool must correlate with a strong logical model base on data driven decision-making.

4.2 Data analysis and results, organized according to the research question(s)

Data Driven Decision Making is a logical model that guides administrators and teachers in making academic decisions for students. Data Driven Decision Making (DDDM) is composed of several resources that guide administrators and teachers in making best practice decisions. The resources that DDDM incorporate are databases and local, state, and federal reports, such as AEIS, AYP, TELPAS, TAKS, PEIMS information. The inclusion of CPAD is another resource related to DDDM. For the purpose of this study, CPAD became the focus because of its abilities to incorporate all of the same information and reports from DDDM into a one-stop-shop, wealth-of-information, database.

4.2.A Research Question #1

1. How is the CPAD organized and what does it look like?

The CPAD data file is a format that is divided into categories such as demographic historical data for each individual student, local information such as special education, limited English proficiency information, present interventions, local benchmarking, mock tests, and state test results. The CPAD data file format is found in APPENDIX (2).

4.2.A.1 CPAD Inputs Logical Model

The components of CPAD include inputs, processes, and outcomes, along with the product of outputs. Each component serves to identify why it is necessary to have these mechanisms within the database as a means of predicting at-risk student academic achievement. The logical model, in response to theory of action, is located in the Appendices (3-9).

CPAD utilizes the software application, Microsoft Excel, as a spreadsheet database. The data entered represents indicators from both state and federal accountability systems. Other indicators within CPAD are representative to the individual cases of each school examined

within this study. Both levels of indicators consist of the following information detailed within CPAD and utilized with each school studied.

4.2.B Research Question #2

2. Through what processes does the CPAD predictive model effectively determine a student's at-risk potential at an elementary level as in comparison to other predictive modeling tools reviewed?

4.2.B.1 Data Driven Decision Making (DDDM)

Data Driven Decision Making consists of resources such as CPAD, Eduphoria database, AEIS, AYP, TELPAS, TAKS, and PEIMS reports. Activities from each of these resources identify students that are gifted and talented, at-risk, special needs, and limited English proficient.

4.2.B.1.a Resources

Resources used in Data Driven Decision-Making (DDDM) are the following: Eduphoria, AYP, AEIS, TELPAS, TAKS, Item Analysis, PEIMS, and TPRI reports. Eduphoria is a set of applications used at Shining Star Independent School District to afford employees the opportunity to generate reports and view data from lesson planning, employee evaluations, local testing results, and it also houses local curriculum. Item Analysis is a breakdown of a Texas Essential Knowledge and Skills (TEKS) objectives and student expectations. See Appendix (3). CPAD incorporates these resources from stand-alone databases to one database, affording administrators and teachers an ability to have one resource that houses in one area each of the mentioned databases and reports.

4.2.B.1.b Activities

Activities for DDDM are as follows: Identifying students such as gifted and talented, at-risk, special education, and limited English proficiency. Tutoring, effectiveness of interventions, test readiness, unprepared versus prepared, teacher effectiveness, staff development, lesson contents of re-teach or re-visit lesson, and early promotion of commended performance are also DDM activities.

4.2.B.1.c Outputs

Outputs for DDDM are as follows: Academic success, TELPAS appropriate exit of students in the bilingual program, teacher awareness of student progress, appropriate individual student goal-setting, progress on accountability measures, effectiveness of adequate coverage of tested curriculum, and identifying individual mastery/non-mastery of the TEKS.

4.2.B.1.d Immediate Outcomes

Immediate outcomes are as follows: Reduce at-risk status of low socio-economic status background and/or challenged ethnic background. Increase likelihood of high school graduation, increase college/career preparedness, remedy academic insufficiencies, properly address academic insufficiencies, and accountability measures met and exceeded.

4.2.B.1.e Long-Term Outcomes

Long-Term Outcomes for DDDM are as follows: Enter post-secondary education, graduate from high school, students equipped with resources, experiences, academic achievement and background to graduate high school and prepared for college and career success, students contributing to society with high expectations, and increasing human capital.

4.2.B.2 Parts of the CPAD Predictive Model

The CPAD predictive model is logically explained through a process that describes how the CPAD database predicts and identifies at-risk students. The premise is to identify students at-risk in elementary school to prevent failure and reduce the risk of high school dropout rates. CPAD is a logic model that describes and explains each of the following areas:

1. Resources needed for the program to function;
2. Activities the program undertakes;
3. Outputs produced from those activities; and
4. Immediate and long-term.

4.2.B.2.a The CPAD Logic Model Defined

To describe the CPAD, a logic model was created to dissect every aspect of the program process of the CPAD. The logic model is explained in a step-by-step process and is shown in Appendix (4-9) to help administrators and teachers in identifying at-risk students at the elementary level.

4.2.B.2.b The Comprehensive, Powerful, Academic Database (CPAD)

CPAD incorporates all aspects of DDDM and is in a predictive logic model in Appendix (4).

4.2.B.2.c Resources

Resources include teachers, administration, instructional coaches, large scale color printer, computer, 11x17 paper, Microsoft Office, TEKS, TAKS scores, mock assessment scores, pertinent data reports, and scanning/scoring software that imports into Microsoft Office Excel.

4.2.B.2.d Activities

Activities are professional learning communities, tutoring, mock testing, campus improvement planning, initial goal setting meetings, follow up/progress towards goals meetings, and meaningful celebrations for meeting goals.

4.2.B.2.e Outputs

Outputs are comprehensive campus data, real time data, flexible data, flexible personalized data reports, comprehensive intervention schedule, and individual student data customized to class period or homeroom placement.

4.2.B.2.f Immediate and long-term outcomes

Immediate and long-term outcomes include: ability to set goals; ability to track progress towards goals; ability to adjust individual student goals, ability to adjust campus goals, incased student attendance; meaningful and consistent data driven decision making; data-driven professional leaning communities discussions, ability to identify strengths and weaknesses; identification of gifted and talented students; appropriate placement of LEP students; appropriate exit of LEP students; early identification of students in need of intervention; the ability to cross compare data that is normally segmented due to lack of comprehensive data systems; increased team effectiveness, building professional capacity; increased likelihood of graduating from high school, consistent progress towards meeting state and federal ever increasing accountability measures, and the ability to rise to challenges of new rigorous assessments.

4.2.B.3 Professional Learning Communities (PLCs)

Professional Learning Communities are groups of administrators and teachers that come together to communicate academic needs for individual students.

4.2.B.3.a Resources

Resources include administrators, teachers, instructional coaches, mock scores, benchmarks, common assessments, and district personnel.

4.2.B.3.b Activities

Activities are as follows: item analysis of every target student, collaboration by PLC to identify weaknesses of student expectations of the TEKS, group students with similar intervention needs, plan tutoring sessions, identify needed resources and materials, plan to re-assess areas of weakness, and adjust students in and out of interventions based on data results.

4.2.B.3.c Outputs

Outputs are as follows: identify areas of weakness on subject area, teachers and administrator actively monitoring student academic success and planning for necessary services based on student need, arrangements for tutoring, testing, goal setting, and staff development and training. Measures of outputs include targeted student's decease after each mock assessment, and weekly PLC meetings to identify students in need of academic interventions.

4.2.B.3.d Immediate and long-term outcomes

Immediate and long-term outcomes are as follows: knowledge of student academic needs, planning tutoring sessions, planning future assessments, purchasing needed resources and materials, knowledge of student preparedness, active monitoring of progress, performance, and curriculum of each student within each classroom as related to resources and materials as necessary for student academic achievement. Measures of immediate and long-term outcomes are conducted through mock tests, common and district assessments, teacher observations, teacher reports, and principal reports.

4.2.B.4 Tutoring

Tutoring is, additional, specified, and remedial interventions given to students in need of academic progress.

4.2.B.4.a Resources

Resources include teachers, instructional coaches, administrators, tutors, school liaisons, classrooms, computer labs, science labs, libraries, and academic software.

4.2.B.4.b Activities

Activities are the following: In-classroom tutoring, after-school tutoring, Saturday tutoring, group tutoring, and individual tutoring.

4.2.B.4.c Outputs

Outputs are as follows: students have academic support and individualized attention to needs, students acquire skills and apply it to increase his/her academic performance. Measures of outputs include tutoring logs, the measurement of areas of weakness, tutoring assessment data, and 9-week grading period outcomes.

4.2.B.4.d Immediate and long-term outcomes

Immediate and long-term outcomes are as follows: student academic performance is improved, students meet academic state criteria, students meet academic assessment criteria, students are promoted to next grade level, students pass state exam with minimal standards, and students pass state exam with commended performance. Measures for outcomes include mock tests, common assessments, teacher observations, TAKS scores, school transcripts, and principal report.

4.2.B.5 Mock Testing (An Assessment used from released State Tests)

Mock Testing resembles state released assessments to facilitate administrators and teachers in determining if students are predicted to pass end of year state assessments for accountability measures.

4.2.B.5.a Resources

Resources include teachers, instructional coaches, administrators, pencils, paper, erasers, scanners/printers, and bubble sheet answer documents.

4.2.B.5.b Activities

Activities include administering tests inside each classroom, separating students based on academic or behavior needs, and same criteria to meet state guidelines for students with special needs, administering tests in same format as "real" state exams, administering mock tests in the following months: October, December, and February, and stipulating that each mock test passing percentages is as follows: October = 45%, December = 60%, and February = 80%.

4.2.B.5.c Outputs

Outputs include student level of performance, identifying weak students relative to certain TEKS-objectives, re-planning tutoring sessions, re-planning goal setting, re-planning staff development, and re-planning training. Measures of outputs are mock assessment data.

4.2.B.5.d Immediate and long-term outcomes

Immediate and long-term outcomes include improved student academic success, improved teacher delivery of lessons, immediate knowledge of student progress/performance, student academic success, and teacher success. Measures include student grades, principal reports, and district assessment reports.

4.2.B.6 Goal Setting Meetings

Goal Setting Meetings are meetings that are held with administrators and teachers to discuss how academic needs will be met for individual students.

4.2.B.6.a Resources

Resources include administrators, instructional coaches, and teachers.

4.2.B.6.b Activities

Activities include keeping the “end” result in the forefront, clearly stating objective accountability, achieving highest potential, and setting differentiated goals for individual students.

4.2.B.6.c Outputs

Outputs include the following: establish, strategize, plan, execute, review. Measures of outputs are as follows: PLC meetings, and mock test results.

4.2.B.6.d Immediate and long-term outcomes

Goal setting activities induce immediate and long-term outcomes to include: motivation, self-confidence, significant, meaningful, attainable, relevant, significant, measureable, action oriented, rewarding, and track-able activities that prepare administrators and teachers to better support student needs. Measures for outcomes are principal reports, mock tests, and TAKS scores.

4.2.B.7 Training and Staff Development

Training and Staff Development are utilized and explored to ensure that teachers are performing and meeting student academic needs.

4.2.B.7.a Resources

Resources include administrators, instructional coaches, teachers, trainers, and presenters.

4.2.B.7.b Activities

Activities include lesson delivery, using the CPAD, item analyses, TEKS standards, meaningful ways to approach new ideas, new technology, new methods, scientific based research, and improve self-efficacy.

4.2.B.7.c Outputs

Outputs include increase in self-efficacy, establishing desired knowledge basis, change, new technologies, addressing shortcomings, enhancing communication, friendly competition, minimizing professional errors, improving professional capacity, motivating and improving teacher retention. Measures of outputs include staff development reports, and teacher participation.

4.2.B.7.d Immediate and long-term outcomes

Immediate and long-term outcomes include knowledge, beliefs, positive attitude, increase in effective skills, motivation, positive behavior, teacher's use of new methods, adoption of new practices, reduction of student failures, broadening teacher perspectives, and the attainment of more knowledgeable teachers. Measures of outcomes include TAKS scores, mock assessment results, common assessment results, and principal reports.

4.2.B.8 How educators make use of the CPAD logic model

The utilization and creation of the logic model process for CPAD was initiated to help the reader better understand CPAD capabilities. The breakdown of each component of CPAD permits educators to gain an understanding of its usage. Each logic model process of CPAD could be construed as difficult for the reader to envision without the ability to break each process into small components for the reader to understand what each process looks like thus, the CPAD

logic model. The CPAD logic model was initiated to help the reader in understanding the incorporation of CPAD and its ability to demonstrate and integrate each process.

4.2.C Research Question #3

1. Through what processes does the CPAD predictive model effectively determine, at an elementary school level, a student's at-risk potential of dropping out of school?

In order to analyze research question three, a 2 x 3 repeated measures ANOVA was conducted. There was one between factor (groups) with two levels. The first level in the between factor was the group who received the CPAD strategies and procedures (treatment group), while the second level was the group who did not receive the CPAD strategies and procedures (comparable group). There also was one within factor (time) with three levels. The first level corresponded to the data that was collected before CPAD was conducted, during implementation, and after CPADs implementation. The dependent variable that was analyzed in this question addressed if students utilizing CPAD (treatment group) were more academically successful than the comparable group.

Results of this analysis yielded univariate results. The design and sample size obtained to conduct this repeated measures analysis makes the interpretation appropriate. According to Maxwell and Delaney (1990) as well as Stevens (2002), this type of analysis is robust against violations to normality, and its F-test is only distorted when there is an extreme deviation from normality. The coefficients of Skewness and Kurtosis for the dependent variables in this research question mostly revealed small to moderate deviations from normality. In cases where extreme deviations from normality are present, effect sizes should be interpreted with caution. For example, extreme skewness in a distribution may produce larger or smaller effect sizes than those that exist in nature.

An examination of the Descriptive information for research question three is presented in Table 5-26. Given that repeated measures ANOVA is robust against violations of normality, a greater emphasis should be interpreted with caution. An examination of the Descriptive information for research question three is presented in Tables 6, 7, and 8. Given that repeated measures ANOVA is robust against violations of normality, a greater emphasis should be placed on addressing issues dealing with sphericity. Therefore, before performing a univariate examination of this same analysis, it is typically considered best practice to examine whether or not the sphericity assumption has been violated (Stevens, 2002). A violation to the sphericity assumption would indicate that the variance of the difference between the estimated means for any pair of treatment and control groups and requires a correction such as the Huynh-Feldt Epsilon, allowing the p values to be more accurate and adjusted upwards by reducing the degrees of freedom (Maxwell & Delaney, 1990). This, in turn, would protect the researcher against making a Type I error or rejecting the null when such should not have occurred (Maxwell & Delaney, 1990). In other words, when the sphericity assumption is violated, the observed *F* value for the test is larger than what it should be and thus, tends to reveal significant differences when none actually exists. Tables 6, 7, 20, and 21 present a graphical representation of the marginal means for this question across treatment conditions and time.

Tables 17, 18, and 19 present the descriptive statistics of treatment groups over time for those students who received the CPAD strategies and procedures. By examining the means and the standard deviations of these two groups one can conclude these groups also are comparable on all demographic characteristics. This comparison was established through the comparable schools report derived from the Academic Excellence Indicator System (AEIS) reports.

Table 5 Descriptive Statistics for the Sample

	Treatment Group	Mean	Std. Deviation	N
TAKS Reading (2007-2008)	Treatment	489.46	217.339	56
	Comparable	631.29	207.528	70
	Total	568.25	222.628	126
TAKS Reading (2008-2009)	Treatment	738.23	186.808	56
	Comparable	789.86	194.079	70
	Total	766.91	191.860	126
TAKS Reading (2009-2010)	Treatment	963.84	189.825	56
	Comparable	1011.07	174.734	70
	Total	990.08	182.383	126

Table 5 represents the Standard Deviation and mean of both Treatment and Comparable groups. The groups mean and standard deviation are reflected over time in the subject of Reading over the school years 2007-2008, 2008-2009, and 2009-2010 for student TAKS scores.

Results from the Box's Test of Equality of Covariance Matrices result in no significance for this assumption, and for the degrees of freedom for both treatment and comparable groups 6 for the treatment group and 97759.576 for the comparable group. The tests of the null hypothesis observed that the covariance matrices of the dependent variables were equal across groups.

Table 6 Mauchly's Test of Sphericity

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound

Time	.939	7.699	2	.021	.943	.965	.500

Table 6 illustrates Mauchly's Test of Sphericity in which the violation of sphericity occurs when it is not the case that the variances of the differences between all combinations of the groups are equal. If sphericity is violated, then the variance calculations may be distorted, which would result in an F-ration that would be inflated. Sphericity can be evaluated when there are three or more levels of a repeated measure factor and, with each additional repeated measures factor, the risk for violating sphericity increases. If sphericity is violated (Epsilon is greater than .75), a decision must be made as to whether a univariate or multivariate analysis is selected. In this case a univariate analysis was selected.

The sphericity assumption in this analysis was examined by using Mauchly's W statistic and such yielded a significant result (Mauchly's W = .939; $p < .01$) which indicates that the sphericity assumption was violated. This information is presented in Table 8.

Table 7 Tests of Within-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
Time	Sphericity Assumed	11357268.829	2	5678634.415	424.124	.000
	Greenhouse-Geisser	11357268.829	1.886	6023200.254	424.124	.000
	Huynh-Feldt	11357268.829	1.929	5887014.180	424.124	.000
	Lower-bound	11357268.829	1.000	11357268.829	424.124	.000
Time * treatmentcontrol	Sphericity Assumed	177352.269	2	88676.134	6.623	.002
	Greenhouse-Geisser	177352.269	1.886	94056.788	6.623	.002

	Huynh-Feldt	177352.269	1.929	91930.141	6.623	.002
	Lower-bound	177352.269	1.000	177352.269	6.623	.011
Error(Time)	Sphericity Assumed	3320497.726	248	13389.104		
	Greenhouse-Geisser	3320497.726	233.813	14201.522		
	Huynh-Feldt	3320497.726	239.222	13880.422		
	Lower-bound	3320497.726	124.000	26778.207		

Table 7 reveals that it was hypothesized and that the utilization of CPAD processes and procedures were significant over time. Even though there was a significant effect for the variable time, overall, results of these analyses was in violation and a Huynh-Feldt test was administered. This test was performed to ensure validity.

Table 8 Tests of Within-Subjects Effects

Source		Partial Eta Squared	Noncent. Parameter	Observed Power
Time	Sphericity Assumed	.774	848.247	1.000
	Greenhouse-Geisser	.774	799.722	1.000
	Huynh-Feldt	.774	818.222	1.000
	Lower-bound	.774	424.124	1.000
Time * treatmentcontrol	Sphericity Assumed	.051	13.246	.910
	Greenhouse-Geisser	.051	12.488	.897
	Huynh-Feldt	.051	12.777	.902

	Lower-bound	.051	6.623	.724
Error(Time)	Sphericity Assumed			
	Greenhouse-Geisser			
	Huynh-Feldt			

Tables 7 and 8 illustrate the tests of within-subjects effects. If Mauchly's test statistic is significant (i.e. has a probability value less than .75) it can be conclude that there are significant differences between the variance of differences: the condition of sphericity has not been met. Fortunately, if data violate the sphericity assumption a researcher must simply adjust the degrees of freedom for the effect by multiplying it by one of the aforementioned sphericity estimates. This will make the degrees of freedom smaller; by reducing the degrees of freedom, the F-ratio is made more conservative (i.e. it has to be bigger to be deemed significant).

Table 9 Tests of Within-Subjects Effects

Source	Time	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Time	Linear	11349185.957	1	11349185.96	701.58	.000	.850
	Quadratic	8082.872	1	8082.87	.762	.384	.006
Time* treatmentcontrol	Linear	139177.624	1	139177.62	8.604	.004	.065
	Quadratic	38174.645	1	38174.65	3.601	.060	.028
Error (Time)	Linear	2005912.455	124	16176.71			
	Quadratic	1314585.271	124	10601.49			

Table 10 Tests of Within-Subjects Contrasts

Source	Time	Noncent. Parameter	Observed Power
Time	Linear	701.576	1.000
	Quadratic	.762	.139
Time * treatmentcontrol	Linear	8.604	.829
	Quadratic	3.601	.469
Error (Time)	Linear		
	Quadratic		

Tables 9 and 10 discuss the data's trend as a linear trend as such is what exists over time and thus best fit the data analysis. This linear trend best fits since it was increasing over time.

Given that the sphericity was violated, the Huynh-Feldt correction was interpreted. There was a significant within-subjects effect for the variable time (F = 701.576; p < .01) as well as for the interaction of the variable time and treatment condition (F = 8.604; p > .01). The effect size for the variable time was small, yielding a partial eta squared of .850.

Table 11 Levene's Test of Equality of Error Variance

	F	df1	df2	Sig.
TAKS Reading (2007-2008)	.208	1	124	.649
TAKS Reading (2008-2009)	.002	1	124	.965
TAKS Reading (2009-2010)	.471	1	124	.494

The Leven's Test of Equality of Error Variance tests the null hypothesis that the error variance of the dependent variable is equal across groups. This test revealed that there was no violation in the comparison of the groups.

Table 11.1 Tests of Between-Subjects Effects

Source	Noncent. Parameter	Observed Power
Intercept	2532.400	1.000
treatmentcontrol	6.861	.739
Error		

Table 11.1 illustrates the unexplainable variances of the treatment and comparable groups and how the implementation of the CPAD made a difference. Both groups have statistical differences between the treatment and comparable scores. The explanation not to not run post hoc tests was because in order to do so, there must be more than two groups.

Table 12 Mean and Standard Error for both Groups

Treatment Group	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Treatment	730.512	22.828	685.329	775.695
Comparable	810.738	20.418	770.325	851.151

Table 12 demonstrates the estimated marginal means of the treatment group was smaller than that of the comparable group, and the standard deviation of error of the treatment group was slightly higher than the comparable group.

Table 13 Mean and Standard Deviation of Error over Time

Time	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
1	560.375	18.998	522.772	597.978
2	764.045	17.112	730.176	797.913
3	987.455	16.277	955.238	1019.673

Table 13 illustrates the estimated marginal means of both treatment groups over time. Table 13 does reveal an increase over time.

Table 14 Mean and Standard Deviation of Error of interaction between Treatment Group and Time

Treatment Group	Time	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Treatment	1	489.464	28.321	433.409	545.520
	2	738.232	25.509	687.744	788.721
	3	963.839	24.265	915.812	1011.866
Comparable	1	631.286	25.331	581.148	681.423
	2	789.857	22.816	744.699	835.015
	3	1011.071	21.703	968.115	1054.028

Tables 13 and 14 illustrate the mean and standard deviation of error of the interactions between both groups and time. As illustrated above, the year the CPAD was implemented for the treatment group; there was a larger increase in student academic success than in the

comparable group. In analyzing the third year component, the treatment group continued to perform better than the comparable group, although CPAD was not fully implemented and maintained during the last year analyzed.

Table 15 Profile plots for TAKS Reading Scores

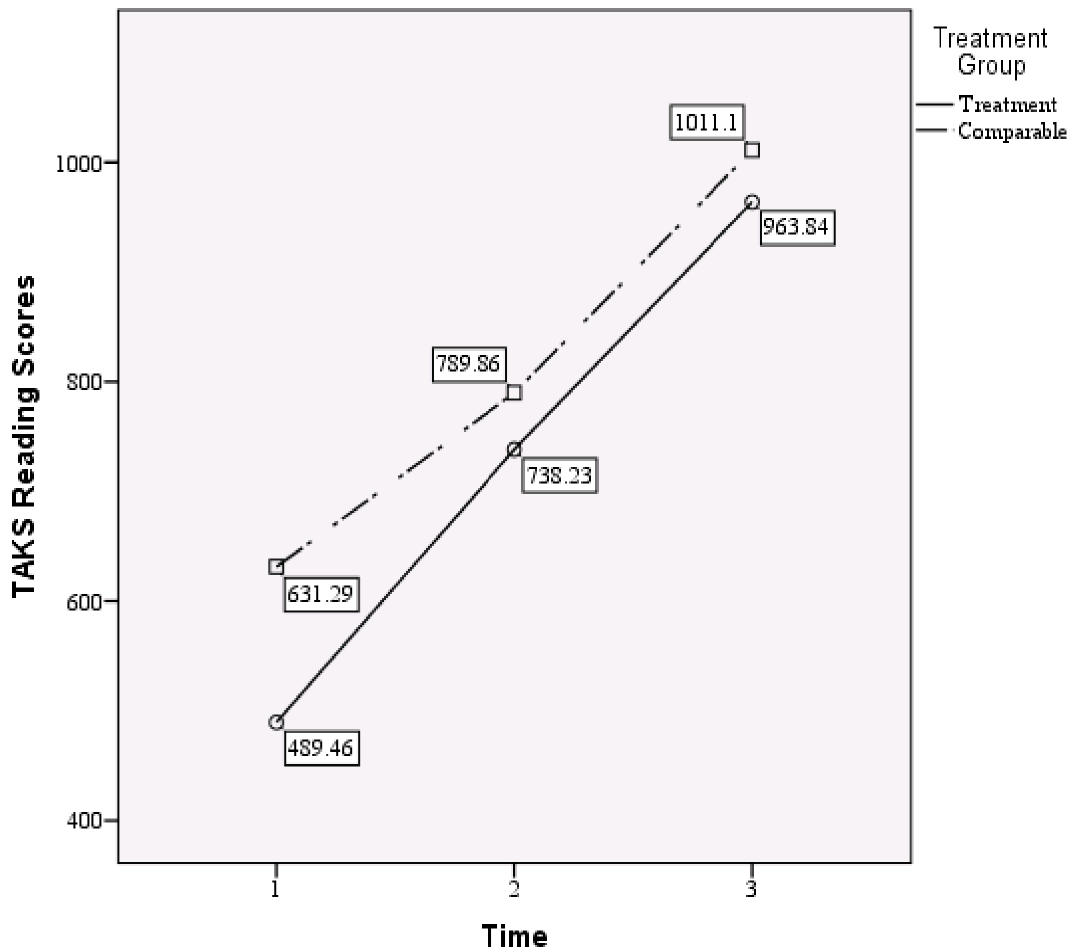

Table 15 illustrates that although the comparable group overall had a higher score in year 3, the treatment group made significant gains throughout years 1 through 3. The comparable group was already at an advantage with a significantly higher score than the treatment group. Whereas, the treatment group made gains of 248.77 from year 1 to year 2, and gains of 225.61 from years 2 to year 3. The comparable group also made gains, however, slightly less than the

treatment group. The gains for the comparable group from year 1 to year 2, and year 2 to year 3 are 158.47 and 222.14 respectively.

Table 16 Descriptive Statistics for the Sample

	Treatment Group	Mean	Std. Deviation	N
TAKS Math (2007-2008)	Treatment	596.53	157.716	59
	Comparable	648.73	185.090	71
	Total	625.04	174.512	130
TAKS Math (2008-2009)	Treatment	740.20	121.596	59
	Comparable	735.28	155.903	71
	Total	737.52	140.865	130
TAKS Math (2009-2010)	Treatment	832.12	111.947	59
	Comparable	844.65	137.564	71
	Total	838.96	126.264	130

Table 16 represents the Standard Deviation and mean of both Treatment and Comparable groups. The groups mean and standard deviation are reflected for student TAKS scores over time, in the subject of Math for the school years 2007-2008, 2008-2009, and 2009-2010.

Results from the Box's Test of Equality of Covariance Matrices result in no significance for this assumption, and the degrees of freedom for both treatment and comparable groups were 6 for the treatment group and 108349.664 for the comparable group. The tests of the null hypothesis observed that the covariance matrices of the dependent variables were equal across groups.

Table 17 Mauchly's Test of Sphericity

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Time	.882	15.969	2	.000	.894	.913	.500

Table 17 illustrates Mauchly's test of Sphericity in which the violation of sphericity occurs when it is not the case that the variances of the differences between all combinations of the groups are equal. If sphericity is violated, then the variance calculations may be distorted, which would result in an F-ration that would be inflated. Sphericity can be evaluated when there are three or more levels of a repeated measure factor and, with each additional repeated measures factor, the risk for violating sphericity increases.

The sphericity assumption in this analysis was examined by using Mauchly's W statistic and yielded a significant result (Mauchly's W = .882; $p < .01$) which indicates that the sphericity assumption was violated. This information is presented in Table 17.

Table 18 Tests of Within-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F
Time	Sphericity Assumed	3004464.488	2	1502232.244	189.555
	Greenhouse-Geisser	3004464.488	1.789	1679734.784	189.555
	Huynh-Feldt	3004464.488	1.827	1644929.856	189.555
	Lower-bound	3004464.488	1.000	3004464.488	189.555

Time * treatmentcontrol	Sphericity Assumed	55236.180	2	27618.090	3.485
	Greenhouse-Geisser	55236.180	1.789	30881.421	3.485
	Huynh-Feldt	55236.180	1.827	30241.543	3.485
	Lower-bound	55236.180	1.000	55236.180	3.485
Error(Time)	Sphericity Assumed	2028810.415	256	7925.041	
	Greenhouse-Geisser	2028810.415	228.948	8861.457	
	Huynh-Feldt	2028810.415	233.792	8677.843	
	Lower-bound	2028810.415	128.000	15850.081	

Table 18 reveals that it was hypothesized that the utilization of CPAD processes and procedures were significant over time. Even though there was a significant effect for the variable time, overall, results of these analyses were in violation, and a Huynh-Feldt test was administered. This test was performed to ensure validity.

Table 19 Test of Within-Subjects Effects

Source		Observed Power
Time	Sphericity Assumed	1.000
	Greenhouse-Geisser	1.000
	Huynh-Feldt	1.000
	Lower-bound	1.000
Time * treatmentcontrol	Sphericity Assumed	.648
	Greenhouse-Geisser	.613
	Huynh-Feldt	.620
	Lower-bound	.457

Error(Time)	Sphericity Assumed	
	Greenhouse-Geisser	
	Huynh-Feldt	
	Lower-bound	

Tables 18 and 19 illustrate the tests of within-subjects effects. If Mauchly's test statistic is significant (i.e. has a probability value less than .75) it can be concluded that there are significant differences between the variance of differences, a correction was embedded and sphericity was not assusmed, as illustrated in Table 20.

Table 20 Tests of Within-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
Time	Sphericity Assumed	3004464.488	2	1502232.244	189.555	.000
	Greenhouse-Geisser	3004464.488	1.789	1679734.784	189.555	.000
	Huynh-Feldt	3004464.488	1.827	1644929.856	189.555	.000
	Lower-bound	3004464.488	1.000	3004464.488	189.555	.000
Time * treatmentcontrol	Sphericity Assumed	55236.180	2	27618.090	3.485	.032
	Greenhouse-Geisser	55236.180	1.789	30881.421	3.485	.037
	Huynh-Feldt	55236.180	1.827	30241.543	3.485	.036
	Lower-bound	55236.180	1.000	55236.180	3.485	.064
Error(Time)	Sphericity Assumed	2028810.415	256	7925.041		
	Greenhouse-Geisser	2028810.415	228.9	8861.457		

	Huynh-Feldt	2028810.415	233.8	8677.843		
	Lower-bound	2028810.415	128.0	15850.081		

Table 21 Tests of Within-Subjects Contrasts

Source	Time	Type III Sum of Squares	df	Mean Square	F	Sig.
Time	Linear	2999964.750	1	2999964.750	351.826	.000
	Quadratic	4499.738	1	4499.738	.614	.435
Time * treatmentcontrol	Linear	25364.750	1	25364.750	2.975	.087
	Quadratic	29871.430	1	29871.430	4.079	.046
Error(Time)	Linear	1091434.865	128	8526.835		
	Quadratic	937375.550	128	7323.246		

Table 21.1 Tests of Within-Subjects Contrasts

Source	Time	Partial Eta Squared	Noncent. Parameter	Observed Power
Time	Linear	.733	351.826	1.000
	Quadratic	.005	.614	.122
Time * treatmentcontrol	Linear	.023	2.975	.402
	Quadratic	.031	4.079	.518
Error(Time)	Linear			
	Quadratic			

Tables 21 and 21.1 reveal the data's trend as a quadratic trend for time and a linear trend for the interaction of time and treatment/comparable groups. This trend as such is what exists over time and bests fit the data analysis. The differences between the groups were not significantly great due to the sample set not having enough power. Power is explained as a magnifying glass and it is difficult to see the significance when there is very little difference in the groups.

Table 22 Levene's Test of Equality of Error Variance

	F	df1	df2	Sig.
TAKS Math (2007-2008)	.081	1	128	.777
TAKS Math (2008-2009)	4.562	1	128	.035
TAKS Math (2009-2010)	2.900	1	128	.091

The Leven's Test of Equality of Error Variance tests the null hypothesis that the error variance of the dependent variable is equal across groups. This test revealed that there was no violation in the comparison of the groups.

Table 23 Mean and Standard Error for both Groups

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter
Intercept	207710911.754	1	207710911.754	4139.686	.000	.970	4139.686
treatmentcontrol	38428.985	1	38428.985	.766	.383	.006	.766
Error	6422466.505	128	50175.520				

Table 24 Mean and Standard Error for both Groups

Treatment Group	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Treatment	722.949	16.837	689.635	756.264
Comparable	742.887	15.348	712.518	773.256

Table 23 and 24 demonstrate the estimated marginal means of the treatment group was smaller than that of the comparable group, and the standard deviation of error of the treatment group was slightly higher than the comparable group.

Table 25 Mean and Standard Deviation of Error of Interaction Between Treatment Group and Time

Time	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
1	622.629	15.258	592.439	652.819
2	737.743	12.454	713.100	762.385
3	838.383	11.151	816.319	860.448

Table 25 illustrates the mean and standard deviation of error of the interactions between both groups and time. As illustrated above, the year the CPAD was implemented for the treatment group, there was a larger increase in student academic success than in the comparable group. In the comparable group, although CPAD was not maintained during the last year analyzed, there were still gains.

Table 26 Profile Plots for TAKS Math Scores

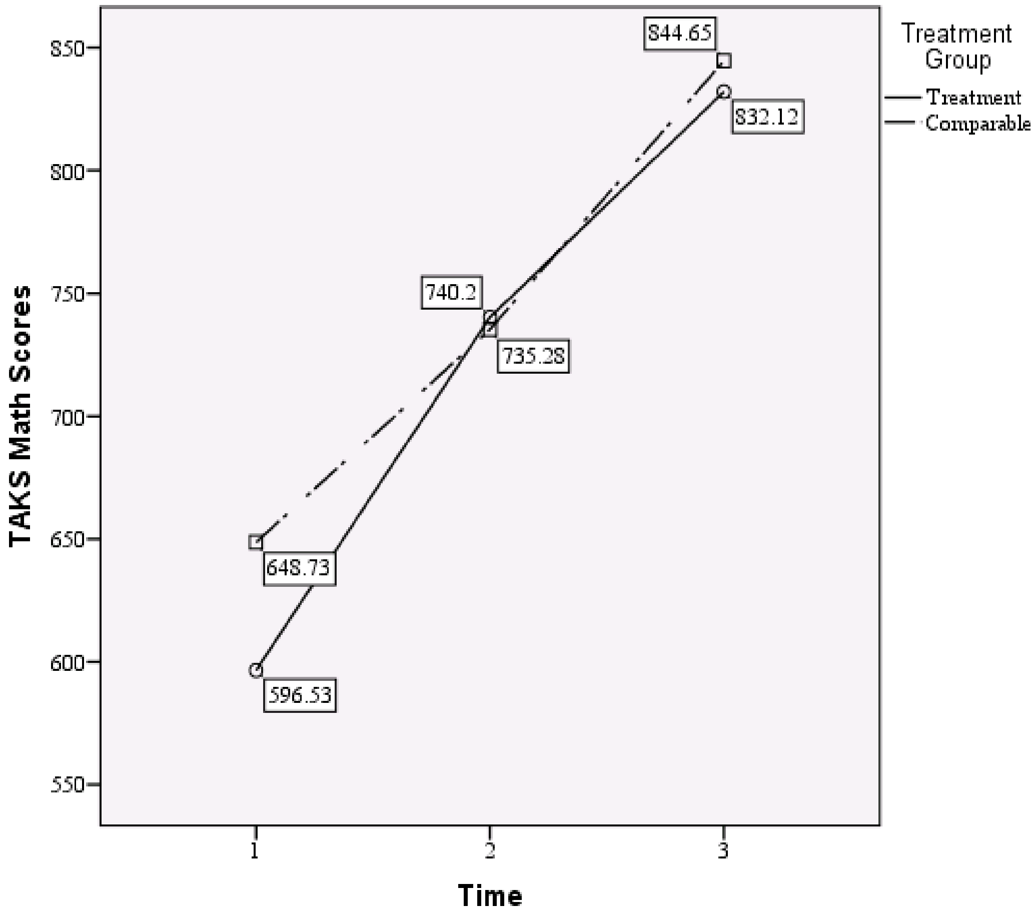

Table 26 illustrates that although the comparable group overall had a higher score in year 3, the treatment group made slight gains throughout years 1 through 3. The comparable group was already at an advantage with a significantly higher score than the treatment group. Whereas, the treatment group made gains of 596.53 from year 1 to year 2, and gains of 832.12 from years 2 to year 3. The comparable group from year 1 to year 2 and year 2 to year 3 are 648.73 and 844.65 respectively.

For Research Question 3, it was hypothesized that the success of CPAD would significantly increase over time and be significantly greater for those that received the CPAD treatment than for those who did not receive the treatment.

Using the CPAD as the primary tool to monitor through progress, curriculum and performance of at-risk student academic achievement facilitates in identifying their need for intervention. "The use of the same progress-monitoring tool before and after special education placement provides a continuous database, increasing the likelihood of understanding the data for all educators and parents, and reducing the training needs for different assessment systems" (Shinn, 2007, p.609).

The CPAD is an ideal tool to utilize in progress and performance monitoring. Not only does it allow for the tracking and monitoring of all students, it provides ease to student data and information, undoubtedly a key component in identifying at-risk students. The "importance of progress monitoring to ensure that teachers are correctly informed of their students' progress throughout the school year. Therefore, the development of a progress monitoring tool which would provide a quick snapshot of students progress and also work in concert with the TPRI, was definitely warranted for Texas Reading First Schools" (Romain, Millner, Moss, & Held, 2007, p. 630).

CPAD is a one-stop tool that can be easily used to track information on all students. It is easily merged into in Microsoft Excel so that all information is readily accessible. It is essential in filtering information, hiding, and unhiding columns. Excel makes reports straight forward and painless. "Recommendations are made for the development of progress monitoring tools that are concise, easy for teachers to use, and that provide clear guidelines regarding the use of progress monitoring data to drive instruction" (Romain, Millner, Moss, & Held, 2007, p. 621). All the other progress monitoring for core content areas are necessary. However, CPAD makes use of the state assessments criteria and works backwards to identify the best resource to use to flex instruction for at-risk students.

Using CPAD not only encourages teachers to understand their students and their academic levels, but to recognize what the students must learn. The understanding of tracking student progress and performance is beneficial. “The primary objective was to present a general framework illustrating the importance and potential value of concurrently tracking changes in students’ performance outcomes along with their beliefs and self-perceptions about their skills to attain these outcomes” (Cleary, 2009, p. 168).

It is evident that CPAD is a progress and performance-monitoring tool that is essential in tracking student progress and related successes. It is imperative that this database be utilized as a valid form of monitoring student achievement so that students can achieve their academic potential. “A major goal was to work toward the development of a seamless and flexible system of progress monitoring. Seamless and flexible implies a system that can be used across students of different ages and skill levels and across settings and curricula. The development of a seamless and flexible system of progress monitoring would require identification of durable measures- measures that would prove valid and reliable across students and settings. The first step in the research program was to review the extensive body of existing CBM research to identify gaps in the research and to highlight areas of need for future research” (Wallace, Espin, McMaster, Deno, & Foegen, 2007, p. 90).

Although Deno, et al., (2009) details another method utilized for the development of a process of universal screening and progress monitoring in reading at the elementary level that would be used in school-wide response to intervention in identifying student’s progress. It undoubtedly is in many respects the same concept as the CPAD. To identify student progress, performance, demographics, testing information, special education, limited English proficiency, and other pertinent information, it is crucial that all the information be kept in one place, one

database. Constant updating and monitoring of the database requires constant monitoring to maintain accurate and valid results relative to the academic success of students. "To create a progress-monitoring system that would fulfill the five necessary functions, teams must decide that it is necessary to measure the performance of all students in fall, winter, and spring. The purpose of those assessments would be to provide the data for growth measurement of all students and enable screening to identify students at-risk for academic failure" (Deno, et al., 2009, p. 47).

The usage of the CPAD is highly promoted as its incorporation has aided in maintaining the recognized and exemplary status of each site researched. However, in a world where empirical data reigns, proof must be based on repeated usage with documented results and must be proved to be of value as an academic instructional tool. As with any academic instructional tool, the question worthy of consideration is: Does it determine or can it extend to educators the ability to see if the database is a valid tool to determine outcomes of academic success through progress and performance monitoring? In other words, if the CPAD actually works, the need to observe it in many areas and at different schools, levels, and with differing demographics is essential. "As with screening, progress monitoring is a central assessment component, because progress monitoring can help determine whether students are responding to intervention. For this reason, educators need information about whether progress-monitoring tools validly index the development of outcomes" (Fuchs, Fuchs, Compton, Bryant, Hamlett, & Seethaler, 2007, p. 317).

4.2.D Research Question #4

1. In evaluating the CPAD, as an early warning predictive model, does it facilitate administrators and teachers, as a data decision-making tool, in the process of identifying at-risk and potentially at-risk students in elementary grade levels?

In the age of state and federal accountability, the ability to predict student academic success is a vital aspect of monitoring and tracking student performance for schools and districts. This procedure helps administrators and teachers determine the needs and areas of concern, as well as implementation strategies that will increase student academic and teacher instructional performance. At the campus level, using CPAD tracks student performance based on each district benchmark, diagnostic test, and weekly common assessments. "Assessment is a vital element in any educational system. States use assessment data to evaluate the effectiveness of their educational systems, school districts use assessment data to monitor the success of their instructional programs, and classroom teachers use assessment data to determine students' strengths and weaknesses in particular areas of the curriculum…"(Stecker, Lembke, & Foegen, 2008, p.48).

This is where the CPAD is essential. Through the data analysis of the TEKS and objectives, administrators and teachers can pinpoint exactly where students are or are not understanding lesson concepts, and the teacher can either re-visit/re-teach or administration can move students to be with the best teacher that will teach the same concept but in a different way for students to grasp content meaning and learning.

As previously examined in Chapter 2: Review of the Literature, students in elementary school can be potential at-risk candidates for dropping out of school (Monrad, 2007; Jerald, 2006). In the state of Texas, there are 13 at-risk indicators to identify students, as identified by

the Texas Education Agency (TEA). These tracked indicators are identified and managed within the Public Education Information Management System (PEIMS). The CPAD utilizes and incorporates at-risk indicators from each of the systems mentioned above that predict student academic achievement by tracking student progress from specific administered state released assessments in each subject area across a set schedule for the school year. The CPAD follows the same theory as the National High School Center (NHSC): There is a continuous need for more research on dropout prevention programs and strategies (Monrad, 2007, p.15). The CPAD also incorporates the works of Jerald (2006) in which early detection warning systems are highly recommended and most crucially needed at the elementary level. "The first step in a proactive approach to stemming dropout is to build an early warning system designed to use accurate data to help target an appropriate mix of interventions for groups and individual students. Such an electronic data system includes individual student-level data that can track students over time and also allow risk factors to be assessed" (p.10).

4.2.D.1 Research Question 4, Sub-Set A

a. As a data decision-making tool, does the CPAD consist of most if not all at-risk indicators, demographics, historical data, and diagnostic test results which can be used to detect at-risk students?

Predicting student academic achievement affords opportunities for administrators and teachers to act on intervention programs that direct the process of identifying at-risk indicators. Through the analysis of the databases examined in Chapter 2, Review of the Literature, the CPAD best suits the purpose of the study in which database reviewed predicted students at-risk of dropping out of school and student academic achievement at the elementary school level. The other databases reviewed focused on graduation drop-out and completion rates, and had very

little information from the research analyzed and reviewed. Most of the outcomes and results of each database reviewed used indicators that would determine student academic achievement.

Other databases reviewed within this study revealed that each database was effective in their own right in determining and assisting administrators and teachers in tracking student academic achievement. However, these types of databases utilized the indicators that are important in predicting high school student dropout and completion rates. However, for this study, the CPAD was the predictive modeling tool that best represented the elementary school campuses researched. This study determined the best predictive modeling tool that aids administrators and teachers in predicting student academic outcomes that benefit students and assessment results.

The databases previously examined in Chapter 2 were analyzed through the lens of which of these predictive modeling tools would best suit an elementary campus in helping administrators and teachers in the identification and implementation of early interventions for at-risk students.

The comparison of the many different database models reviewed can be found in Appendix (1). The models reviewed, based on the criteria and standards of the state of Texas and federal accountability measures for assessments at the grade levels in elementary school, were comprised of at-risk indicators, demographic information, historical data, current assessment results, and results from released state assessments. Each model reviewed was identified as being a model in use in educational institutions that facilitate their utilization for decision making purposes. Each model reviewed additionally analyzed the at-risk indicators determined by both state and federal accountability standards and measures. Each model analyzed and reviewed was then placed in a spreadsheet indicating which model best represented

the criteria and standard for administrators and teachers at the elementary school level, and were furthermore given a check mark indicating that each individual model met or did not meet the criteria/standards. The results of this comparison can be found in Appendix (1).

4.2.D.2 Research Question 4, Sub-Set B

b. As a data decision-making tool, does the CPAD identify at-risk students from each tested grade level and each tested subject to predict student mastery/non-mastery, and how is it communicated?

The CPAD was the model that met the criteria for implementing the most standards based on state and federal accountability measures. From these results of the CPAD, it was determined that through the utilization of this predictive modeling tool, administrators and teachers were able to determine, with early detection, which students met the at-risk indicators of possible failure in future state assessments. The processes of the CPAD implementation as utilized as a predictive modeling tool in the identification of at-risk students, the identification of the response to intervention, and the processes and procedures of interventions through curriculum and instruction, determined student passing rates as well as a longitudinal analysis of student academic growth relative to state accountability measures. Communication is through PLC's and goal-setting meetings.

4.2.D.2.a Factors Included in the CPAD Database

Several components framework the predictive model. Furthermore, administrators and teachers determine what historical, demographic, and other information is deemed necessary by each individual campus to be inputted into a predictive modeling tool. All information inputted into a predictive modeling tool must be converted to the program language and the criteria needs of the utilized predictive modeling tool. Such affords administrators and teachers opportunities

to predict students most at-risk of failing to advance toward increased student academic achievement. The data inputted included state and federal at-risk indicators, and assessment guidelines of pass/failure rates.

4.2.D.2.b Assessment Data

Schools, in this study, were assessed throughout the academic year using data results obtained from weekly common assessments, as well as district and campus benchmarks. Assessment data was formulated to predict student outcomes by incorporating state and federal calculations on how each entity measures student academic achievement. Administrators and teachers were the end users who monitored, reviewed, and acted upon results of the predictive model. Predictive modeling tools must have an easy to use dashboard that will produce easy to use reports. Although CPAD is at an early stage of technological production with limited dashboard abilities, it is capable of rendering important reports. The flexibility of CPAD relates to the incorporation of a Microsoft Excel spreadsheet, which can be easily utiliezed by personnel at the elementary school level, thus affording opportunities that will personalize CPAD to fit specialized educational needs. The ability to convert CPAD from a dashboard into an Excel spreadsheet and vice versa clearly communicates how flexible CPAD can be, and further reveals the ability to personalize individual student campus needs. Reports must be useful, with ease of utilization by administrators and teachers in their efforts to review and determine levels of interventions necessary for each individual student. The assessment data used to predict student academic achievement obtained by predictive modeling tools must incorporate student assessments. The assessments administered to students resemble state assessments, ensuring better, valid, and a more true prediction of assessments administered throughout the school year. "In addition to one-time screening measures, schools may implement benchmark assessment

systems in which all students are assessed at several points during the school year. Similarly, teachers examine student scores to identified benchmarks that indicate relative risk status for reading failure" (Stecker, Fuchs, & Fuchs, 2008, p. 11). Understanding weekly common assessments, district benchmarks, and released TAKS tests certainly aid administrators and teachers as they monitor student progress and success, along with understanding the importance of each of these types of assessments.

4.2.D.2.c Common Assessments

Common assessments are administered to students after the teacher has presented the lesson of the taught objective. Teachers can determine if students understand the lesson presented by administering a common assessment at the conclusion of teaching the lesson concept. Depending on the scores students earn administrators and teachers determine what is acceptable for a passing percentage. Some campus administrators and teachers determine that 70% is a mastery rate. However, some expect the passing percentage to be at the 90% level. The methodology should be striving for 100% at all times, nothing less, thus exhibiting high expectations as a projected norm.

4.2.D.2.d District Assessments

District benchmarks are determined by district expectations, with a score of 70% being designated as the mastery rate. However, it is highly recommended that students should score a minimal of 85% on district benchmarks. Released Texas Assessment of Knowledge and Skills (TAKS) assessments, depending on what time during the school year they are administered; will determine the level of percentage to predict student academic achievement. Student accountability for scoring a 90% on an end-of-year test in October, would equate to only an introduction of 2 months out of 7 months of the math curriculum, and 2 months of the 5 months

of the reading curriculum. "Teachers need more than measures to serve as indicators of student performance and learning trajectories; they also need evidence-based practices to implement when current instructional methods are not producing desirable results" (Foegen, 2008, p. 65). Many of the benchmark data utilized at district levels are not usually scientifically researched based in data collection. Therefore, data may be presumed as unreliable and possibly invalid. The abilities and purpose of these benchmarks are to render a substantial expectation to verify if campuses are meeting presumed state accountability measures. The utilization of CPAD and the flexibility powers it provides can be monitored progressively to ensure that district assessments are meeting accountability measures that present important clues for administrators and teachers to vary differing assessment tools that benefit any school district. These clues that are presented to administrators and teachers are based on the data collection of such said benchmarks along with scores from state assessment data that when converted through scatter plot graphs present a correlation between benchmark performance and state assessment performance. CPAD utilizes the flexible capabilities of an Excel spreadsheet which affords administrators and teachers abilities to significantly monitor student academic success, along with the reliability of district benchmarks in meeting state accountability measures.

4.2.D.3 Research Question 4 Sub-Set C

c. As a data decision-making tool, does the CPAD and its processes and procedures identify key components, which pinpoint beneficial and meaningful interventions?

The CPAD processes, analyzed through the utilization of a logical model, consists of many inputs and outcomes. The most common processes for administrators and teachers to

follow for identifying at-risk students and thus increasing student academic achievement are detailed in the next paragraph:

Progress and performance monitoring are key components in identifying at-risk students. Administrators and teachers assess their students in several ways throughout the school year. However the main focus of the decision making process is composed of the three mock tests administered to students during the school year to record and monitor academic growth and achievement. The administration of the first mock test is during the month of October. This affords teachers the opportunity to present, at the minimum, nine weeks of the curriculum. The results of the administered released TAKS test determines how much of the presented curriculum students have mastered and comprehended. Only the previously taught instructional content and the essential knowledge and skills are analyzed. It can be determined that students that have not been introduced to taught material will possibly not perform to expectations and therefore such is not calculated into predictive passing score percentages. Students that are not meeting the passing percentage for the first mock test at the 45 percentile range are flagged and immediately identified as needing interventions. Individual item analysis is then utilized to pinpoint the areas in need of interventions in a particular subject area tested, within a particular grade level. Item analysis includes a verbal descriptor of actual learning objectives, which entails a quick reference to what the student expectation and objective actually entails, versus an uncommunicative numeric value. A second mock test is usually administered in December before students are released for holiday break. During this time, the mock testing percentile predictive passing score is increased from 45% to 55%. The same item analysis process is followed to determine if students targeted for intervention are responding to the interventions. The second standard of 55% is also used to determine if additional students need interventions. Students scoring above

55% are predicted to pass the actual state assessment. Predicted passing rates are calculated and based on the number of students who are predicted to pass or fail. This predicted passing rate can help administrators and teachers determine which students will meet state and/or federal accountability measures. If predicted rates are positive, a campus team can feel reassured that everything instructionally is working and they can then proceed. If not, then school personnel can adjust and use professional learning community's processes to determine necessary actions. The consistent and constant monitoring of performance, progress, and curriculum is crucial in determining if students are meeting academic expectations.

4.2.D.3.a Data Decision Making Tool Curriculum and Instruction Intervention

Interventions are determined based on student results on the mock tests. Key components to the intervention are: 1) determining pinpointed areas within the curriculum that are identified as weaknesses, and 2) responding appropriately through the implementation of an item analysis for each student. An item analysis relates to the student expectation based upon the determined released state assessment objectives and standards from the Texas essential knowledge and skills for each determined grade level and subject. Through the item analysis process, administrators and teachers are able to pinpoint areas which students will be unsuccessful whereby meaningful interventions can occur. Once student weaknesses are identified, administrators and teachers focus on specified TEKS, learning objectives, and student expectations, and afford students multiple opportunities, via differing teaching and learning strategies and techniques, to master various criteria. These strategies and techniques are not the focus of this study, but a crucial part of the implementation of the CPAD and thus, meeting student academic success.

Predicting student academic achievement, based on historical data and recent assessment results, affords administrators and teachers the opportunity to intervene immediately when

working with struggling students. “We suggest that desirable practice also includes teaches conducting progress mentoring with entire classes periodically to judge whether all students are progressing as they should. Schools will need to determine how to support teachers in using progress monitoring data to strengthen their own instructional practices and to interpret whether accommodations and modifications made in the core program have desired effects on particular students or groups of students” (Stecker, Fuchs, & Fuchs, 2008, p. 10). Progress monitoring of academic success for all students within the elementary state and federal accountability grade levels is essential for teachers to evaluate students and to determine if instruction is effective and therefore meets pre-determined expectations for students.

4.2.D.3.b Response to Intervention

Administrators and teachers that utilize predictive modeling tools facilitate the process of quickly identifying at-risk students. Students identified as not performing to expectations are placed in intervention programs. Each elementary campus administrator and teacher may utilize numerous levels of interventions to guide and facilitate students toward academic achievement. If students are weak in curricular concepts, simple changes, such as lesson delivery may be an intervention. A cohort of teachers, within a grade level, can share lesson delivery and collaborative ideas based on results of assessments administered to each grade level student. The grade level teachers are able to compare, through the process of item analysis, how students did on each Texas Essential Knowledge and Skills (TEKS), objective, as well as another student expectation on any given assessment. By identifying the teacher whose assessment results revealed the highest student scores for each TEKS objective and student expectation, said teacher can then facilitate a process by which the other teachers within the teaching cohort can better apply learned lesson concepts to all students within the grade level. As administrators and

teachers share and receive the best instructional methods for students to achieve academic success, a strong team building and communication process at the grade level will ensure academic success for all students. The Shining Star Independent School District (SSISD) incorporates a Response to Intervention model to help with monitoring student's progress. However, this model is limited only to response and does not incorporate all necessary methods such as the CPAD predictive logic model. To be successful, administrators and teachers monitor student success from the first day the students enter the classrooms. Curricular focus plans worked for SSISD, and allowed for administrators and teachers to follow the curriculum determined as it was taught in incremental segments. Throughout the school year, administrators and teachers determined what Texas Essential Knowledge and Skills (TEKS) must be presented and mastered at specific time periods. Analyzing student's assessment results by item analysis, and measuring each individual student expectations, teachers and administrators were able to obtain results which were crucial in determining necessary interventions for individual students. This was a benefit of CPAD incorporation and utilization.

4.2.D.3.c Levels of Intervention

Predictive modeling tools assist administrators and teachers in the prediction of at-risk students who may not meet standards of increased academic achievement. Teachers are very important in the predictive and intervention process of students. Teachers recognize student weaknesses and thus help refine the intervention process. Students identified as being at the "at-risk Tier 3" level for academic achievement are identified as students that are not being successful with classroom instruction, small group and or one-on-one targeted tutoring. These students can be evaluated for academic deficiencies and referred, for example, to special education. "Additionally, educators are also encouraged to use their professional judgment on a

case by case basis when deciding whether students qualify for Tier 3 instruction" (Romain, Millner, Moss, & Held, 2007, p. 623). The ability to place students into tiers, as a method of identifying at-risk student levels of achievement, has proven to be a beneficial model to follow. "A second layer of instruction increasing the intensity of key reading components may then be provided by a highly trained teacher in addition to instruction. The third layer of instruction, if needed, should be highly research-based and systematically and explicitly delivered in addition to the instruction in the first two layers" (Moore & Whitfield, 2009, p.622).

Although much of the research within this study focuses on reading and mathematics, many of the strategies of intervention pertain to other academic subjects. SSISD utilized the three-tier methodology or process to categorize students by academic progress. The three tiers are defined below:

Tier 1 is for all students whether they are special or regular education and identifies these students as being on target and understanding the academic concept.

Tier 2 is for struggling students that have a basic understanding of the concept of a particular context of information. However, these students have certain educational gaps that need to be addressed.

Tier 3 is the most intensive level of intervention. Groups of students at risk of failure are analyzed through scientific data. Administrators and teachers place these students into specified intervention groups. The CPAD predictive logic model is a tool to utilize when identifying students that are at-risk of obtaining academic achievement.

Students can be in any of the first two tier levels at any time. The levels of intervention may change after each lesson is taught in any subject. However, with consistent and constant progress and performance monitoring, administrators and teachers can determine if Tier 3

interventions are working, and if necessary, implement the process for identifying students that may require special services to succeed. The CPAD approach can facilitate in the process of identifying students on a weekly basis through common assessments and after the administration of each campus or district diagnostic/mock test.

Tier 1 is to respond to the needs of every student that is on level. Tier 2 is designed to help with struggling students who have some difficulties, and Tier 3 is designed to target those students with definitive struggling tendencies that need to be addressed immediately with targeted interventions. The first point of contact to be able in determining tier-level information comes from the homeroom teacher. "The first level of instruction is provided by the general education classroom through a teacher who uses data-based decisions to inform instruction" (Moore & Whitfield, 2009, p.622).

4.2.D.3.d Monitoring the Early Years

"Although many complexities exist regarding which assessments, or combinations of assessments, may be used for each of the four aforementioned assessment purposes, one complexity regarding progress monitoring continues to raise concern and is therefore the impetus for this study. Beginning in kindergarten and extending to Middle of Year (MOY) grade 1, state guidelines require that teachers use their classroom-based instructional assessments for progress monitoring." (Romain, Millner, Moss, & & Held, 2007).

SSISD allows for CPAD to assess students to determine their academic level. This determination provides for a first level of response to interventions that students may need, and further guides instruction relative to each of the Tier levels. Administrators and teachers at the treatment elementary school have divided each level into 3 Tiers as previously examined.

4.3 Summary

Results of the data collection as well as the CPAD logic model provides detailed and significant information that benefit administrators and teachers in making data driven decisions for at-risk students. In answering the research questions in Chapter 4, many components will be discussed in the next chapter. Chapter 5 entails discussions that relate to the Findings, Generalizations, and Implications.

Chapter 5: Conclusions

5.1 Introduction

This chapter includes a summary of the study with findings, generalizations, limitations, implications, and recommendations for further research. This study examined the effectiveness of CPAD at the treatment campus versus the comparable campus, by examining at-risk student academic achievement in the subject areas of reading and mathematics over a three year period. The following research questions guided this study:

1. How is the CPAD organized and what does it look like?
2. Through identifying the processes of the CPAD logic model, do the CPAD processes model an effective tool in determining outcomes for an elementary school student's academic achievement as in comparison to other predictive modeling tools reviewed?
3. Through what processes does the CPAD predictive model effectively determine, at an elementary school level, a student's at-risk potential of dropping out of school?
4. In evaluating the CPAD, as an early warning predictive model, does it facilitate administrators and teachers as a data decision-making tool in the process of identifying at-risk and potentially at-risk students in elementary grade levels?
    a. As a data decision-making tool, does the CPAD consist of most if not all at-risk indicators, demographics, historical data, and diagnostic test results which can be used to detect at-risk students?
    b. As a data decision-making tool, does the CPAD identify at-risk students from each tested grade level and each tested subject to predict student mastery/non-mastery, and how is it communicated?

c. As a data decision-making tool, does the CPAD and its processes and procedures identify key components which pinpoint beneficial and meaningful interventions?

The subjects selected for this study was an elementary school that utilized the CPAD strategies and a comparable elementary school that did not. This study measured at-risk students academic achievement by comparing TAKS scores of the treatment elementary school with the comparable school.

5.2 Findings

The CPAD is organized into individual segments. The data file format can be reviewed in Appendix 2. Each segment is sub-divided into larger segments of student data collection that reveal the following:

- Demographics
- Local campus and district information
- Academic assessments
- Language acquisition assessment
- Special needs coding and recommendations
- Response to interventions for academic subjects
- Response to interventions for language acquisitions
- Historical assessment data prior to state tested years
- TAKS scores for Reading by objective
- District Benchmark scores for Math
- Response to interventions for academic subjects
- Response to interventions for language acquisitions
- Historical assessment data prior to state tested years
- TAKS scores for Math by objective
- District Benchmark scores for Science/Writing
- Response to interventions for academic subjects

- Response to interventions for language acquisitions
- Historical assessment data prior to state tested years
- TAKS scores for Science/Writing by objective
- District Benchmark scores for Science/Writing
- Weekly Reading intervention assessment scores
- Weekly Math intervention assessment scores
- Predictive measures for state accountability for Reading
- Predictive measures for state accountability for Math
- Predictive measures for state accountability for Science/Writing
- Predictive measures for federal accountability for Reading
- Predictive measures for federal accountability for Math
- Predictive measures for federal accountability for Science/Writing

The processes of the CPAD include:

- Professional Learning Communities
- Tutoring
- Mock Testing
- Goal Setting Meetings
- Staff Development/Training

The CPAD is utilized as an effective predicting modeling tool at the elementary school level to improve academic achievement for at-risk students. Values for the treatment and competitive groups were compared for each of the subsets using a 2 x 3 repeated measures ANOVA. A significant difference was found in the attrition rates among the participating

campuses. A general linear model utilizing a repeated measure ANOVA was used to determine the significance of a possible relationship between all school years.

Through the processes of CPAD predictive modeling capabilities the CPAD logic model details how the CPAD data file format is utilized through an association with a DDDM logic model, to demonstrate how CPAD is an effective predictive modeling tool. When utilizing all of the CPAD monitoring strategies and procedures the result is improved academic achievement for at-risk students. This assertion relates to the values for the two groups as compared for each of the subsets using a 2 x 3 repeated measures ANOVA.

To investigate the second and third research questions as to whether or not a significant difference existed in the attrition rates of treatment and comparable schools, the TAKS reading and math lexile/quantile scores respectively were compared. An ANOVA repeated measure utilizing a multivariate analysis was incorporated to determine the significance of a possible relationship between all school years. The determined results and levels of significance are addressed in the Generalizations section (see page 112) of this chapter.

In evaluating CPAD, as an early warning predictive model, it was demonstrated that the model aided administrators and teachers as a positive and proactive data decision-making tool in the process of identifying at-risk and potentially at-risk students in elementary grade levels. As a data decision-making tool, CPAD consisted of most if not all at-risk indicators, demographics, historical data, and diagnostic test results which could be used to detect at-risk students. As a data decision-making tool, CPAD identified at-risk students from each tested grade level and each tested subject to predict student mastery/non-mastery, and it was communicated to administrators and teachers, with proven results. As a data decision-making tool, CPAD and its processes and procedures of implementation identified key components, which pinpointed beneficial and meaningful interventions. In the review of Data Decision Driven Making logic

model and the logic model of CPAD as found in the appendices section (see Appendices 3-9), an illustration is provided as to how administrators and teachers can follow the logic model for optimal utilization for implementation at a school. Within these appendices the reader can visually understand the CPAD predictive logic model's abilities to aid administrators and teachers in identifying, intervening, and affording opportunities for at-risk students so that these students are academically successful. CPAD's ability to help administrators and teachers in combating the high level of high school dropouts focuses on a proactive approach and intervening in the elementary school years, where possible at-risk identification begins. The understanding that students do not become at-risk in high school clearly reveals that if educators are involved in proactive measures to minimize students becoming at-risk, the proactive approach must begin in the early years of the student's educational career. Identifying at-risk students at an early stage in their educational careers, helps minimize educational gaps, and therefore, reduces high school dropout rates.

In regards to the second and third research questions of whether or not a significant difference existed in the academic achievement of students in reading and math over the course of the treatment year, the evidence gathered indicated that in general the differences were significant. In all of the comparisons involving data collected from Reading and Math assessments, a statistically significant difference was found in the mean of CPAD values. There were statistically significant differences that were found for Reading in year 2 and year 3, from the students in the treatment school group. Although, there were significant differences that were found for Math in year 2 and year 3, the significance was not statistically greater than in Reading. Therefore, it is substantiated from these data that the treatment group of students, was more effective in Reading than in Math. In terms of affecting student achievement, the treatment group performed statistically the same as the comparable group. In the subject of

mathematics, however, students in the treatment school group showed minor, yet statistically significant, greater growth than students in the comparable school group, but only in year 2, when the CPAD was implemented. In the remainder of the analysis involving Reading and Mathematics achievement there was statistically significant differences in student growth based on the utilization of CPAD.

5.2.A A Layman's Model of Study Revelation

As a means of better understanding the complexities of the findings section within this chapter, examine the bulleted listing below. This study revealed students at-risk of failure:

- Did better in Reading than Mathematics with the incorporation of CPAD;
- Although both subject areas (Reading and Mathematics) had significant growth, the Treatment group experienced significant growth periods (one point in time to another) than the Comparable group.
- In respect to understanding the Treatment group, this group began the study significantly lower in their scores (for both Reading and Mathematics) than the Comparable group in year 1.
- During year 2, the Treatment group surpassed the Comparable group in both Reading and Mathematics.
- In year 3, the Treatment group maintained higher scores in Reading than the Comparable group and was only slightly lower than the Comparable group in Mathematics.
- Overall, the following determination can be surmised regarding CPAD:
- If utilized effectively (following the data file format [see Appendix 1] and the logic model [see Appendices 3-9], CPAD can improve academic success in Reading and Mathematics for students at-risk of failing Texas state accountability assessments.

- Administrators and teachers have abilities to generate knowledge to assist students in academic success through the processes of monitoring student's progress, performance, and curriculum.

5.3 Generalizations

The generalizations of this study consider abilities of replication of CPAD at local, state, and national levels. CPAD could easily be replicated in the state of Texas, with some slight modifications. CPAD could easily be manipulated to fit the needs of any Texas school district or campus.

Replicating CPAD for another state or at the national level would require significantly more intense modifications to include incorporation of state-specific objectives, common course standards, and state assessment standards and objectives. These modifications could be implemented within the data-file format, and by following the state or national assessment accountability measures.

5.4 Limitations

The limitations of the study were associated with maintaining a minimum of 30 students from each sample site. Due to high mobility rates, the schools studied were the only 2 schools that maintained such a set sample. The researcher had a total of 4 other campuses to review, but was unable to maintain, in their schools, the minimum sample set size.

Another factor affecting the comparison across each researched school year was a noticeable amount of excluded student information. Test types were tied to TAKS only, and therefore left eleven students that were administered a different test type. Seven students had testing result blanks in their examination history. This could be related to an unknown reason such as school attendance-absenteeism.

The inability to inform the readers about how each of the formulas are utilized within the CPAD database and how each of these formulas predict at-risk student academic success and how each of these formulas were derived are limitations. Modifying these formulas to other state assessments could be done. Therefore, such considerations serve as limitations. Further limitations could be related to the inabilities of factoring in the demographics of students' baseline knowledge, gender, emotional and social needs, intelligence, intervention processes, and language. A final limitation could very well be the researcher's conscious and unconscious bias. While, few individuals can completely achieve objectivity in research, the greatest limitation, even temptation, in this study was the possibility of the researcher developing a favorable attitude of the CPAD database. Favorable feelings regarding CPAD were likely consequences and thus could contribute toward positive biases based on the researcher's past incorporation and utilization of the CPAD database. Additionally, the researcher had, previous to the study, developed a professional relationship with the designer and creator of the CPAD. Each of these limitations is indicative of the need for future research.

5.5 Implications

The most obvious implication of the findings of this study stem from the ability to translate and convert CPAD into a viable and useful technological tool that is user friendly. The usability engineering five-step process sheds light onto this transition and gives a recipe for action. Five actions to begin a systematic approach to usability could be followed:

- Recognize the need for usability in an organization.
- Ensure that usability has management support.
- Devote specific resources to usability engineering, i.e., user-friendly dashboards for individuals that may not be computer literate.

- Integrate systematic usability engineering activities such as inputting student historical, demographical, and local campus assessment information, into the various stages of the organizational development lifecycle
- Ensure that all user interfaces are subjected to user testing (Nielsen, 1993).

The slight differences in student academic achievement, which this researcher did find to be significant, suggest that at-risk students in the treatment group had more growth than the students that did not utilize the treatment. This may be significant for administrators and teachers relative to implementation of the procedures and strategies of CPAD. The findings of this study suggest that these students might gain a benefit (albeit small) from utilizing CPAD.

The Academic Excellence Indicator System has reports that detail the report card scores of the Texas Education Agency for both treatment and comparable schools. CPAD offers school districts a readily available value added model from which to identify trends in student achievement that provide a much more insightful perspective of the effectiveness of district initiatives than simply examining passing rate.

The refinement of a value added model of student achievement specific to a given school district requires accurate and plentiful data in order to confidently reveal trends. The numbers of student relative to Reading and Math assessment scores, which are required to make comparisons and conclusions, underscores the need for school districts to maintain accurate records, not just of student assessment data, but of historical connections between students and teachers.

The ability to generalize findings about CPAD based on at-risk student academic achievement could be greatly facilitated by centralized efforts from the state education agency. The agency has the ability to maintain data as related to students and teachers.

The researched schools utilized the entire strategies and processes of CPAD during the implementation year. The results of the study, located in Chapter 4, reveal that the effectiveness of implementing CPAD and all of its resources equates to increased student achievement.

5.6 Recommendations for Further Research

While not of statistical significance at the 95% confidence interval, the p=.060 significance of the difference in mean achievement between treatment and comparable school groups in both reading and mathematics warrants further research, perhaps using different demographic or contextual variables.

Similarly, the p=.076 significance of the difference in elementary mathematics achievement offers possibilities for further investigation in determining student academic achievement through middle school assessments.

Additionally, the p=.004 significance of the difference in elementary reading achievement offers possibilities for further investigation in determining student academic achievement through middle school assessments.

Additional studies are needed before more profound generalizations regarding the effectiveness of CPAD, as measured by at-risk student achievement, can be made. Of the schools that were originally intentioned to be subjects for this study, only a fraction were utilized due to high mobility rates. Such limited the researcher in comparing a larger sample set of student achievement scores.

The need exists to collect and maintain longitudinal data regarding student assessment scores and student achievement. Further efforts by researchers in maintaining data for this purpose may yield undiscovered findings. The Texas STAAR assessments, new to the Texas accountability system in 2011, will offer tremendous opportunities to directly link CPAD with student assessment data at the elementary school level.

While analyzing data for this study it was discovered that greater differences in achievement existed between the treatment school as compared to the comparable school. Such may suggest that utilizing CPAD may play a greater role in affecting at-risk student academic achievement.

The openness and ability to improve the CPAD database, logic model strategies and procedures, are always at the forefront of every practitioner/researchers mind. Conforming and creating a better utilization of the CPAD tool to enhance its abilities will continue to be guided by state and federal educational laws as well as the end-users that utilize the database to facilitate the needs of their students.

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Appendix 1

		PREDICTIVE MODELING DATABASES THAT ARE AVAILABLE							
		DIBELS	EWDS	CPAD	LONESTAR	NEDM	SEDL	RAND	SLDS
PROGRESS, CURRICULUM, PERFORMANCE, AT-RISK BOTH LOCAL, STATE, AND FEDERAL INDICATORS	Semester Course Failures		√		√				
	GPA/Grades		√		√	√			
	Earned Credits		√		√				
	Attendance		√			√			√
	Retention		√	√	√				
	Disengagement								
	State (assessment) performance		√	√	√	√	√	√	√
	Race		√	√		√	√	√	√
	ethnicity		√	√	√	√	√	√	√
	Socio-economic status		√	√					
	Special programs (SPED, GT,...)			√					
	gender	√	√	√	√	√		√	√
	Literacy assessments	√		√					
	Math assessments			√					
	Science assessments			√					
	Benchmarks local/campus level			√					
	Common assessments local/campus			√					
	Discipline								
	LEP/ESL/ELL		√	√		√	√	√	√
	Federal (assessment) performance		√	√	√	√	√	√	√
	Early Childhood assessments	√		√					
	Interventions local			√					
	Teacher identification (past/present)			√	√				
	Prior school history (location of state/country)			√	√				

Appendix 2

CPAD Field Description

Comprehensive Powerful Academic Database Summary Data File

Information presented in this file is the data from the CPAD database. Each record on the file is for a given grade, summary type, record type, and category type. Aggregated information contained in the Confidential Summary Data File is from TAKS and TAKS (Accommodated) assessments only. TAKS-Modified results are excluded.

Location From-To (Column)	Field Length	CPAD Field Description
A	Open ended	Last Name
B	Open ended	First Name
C	2	Section of grade/teacher. (Example: 1A = Gibson, 2C = Chavez)
D	2	Section of grade/teacher. (Example: 1A = Gibson, 2C = Chavez)
E	2	Section of grade/teacher. (Example: 1A = Gibson, 2C = Chavez)
F	2	Section of grade/teacher. (Example: 1A = Gibson, 2C = Chavez)
G	2	Section of grade/teacher. (Example: 1A = Gibson, 2C = Chavez)
H	1	Sex: M=Male F=Female
I	8	Date of Birth (Example: 10/12/1953)
J	10	School local identification number
K	1	Title 1, Part A Y=Yes Leave all other blank
L	1	Section 504 Y=Yes Leave all other blank
M	2	Grade Level of prior school year
N	1	Past Retentions Y=Yes Leave all other blank
O	1	Past Retained/Conditional Y=Yes Leave all other blank
P	1	At-Risk Y=Yes Leave all other blank
Q	21	At-Risk Reason

		RD=Failed Reading LEP=Limited English Proficient HM=Homeless
R	1	Migrant Y=Yes Leave all other blank
S	1	Pupil Transfer Y=Yes Leave all other blank
T	1	Immigrant Y=Yes Leave all other blank
U	1	Economically Disadvantaged Y=Yes Leave all other blank
V	2	Ethnicity H=Hispanic AA= African American W=White A=Asian I=American Indian O=Other/More than two
W	1	STAT Status (Student Success Team) Student is in interventions (Tier II, Tier III)
X	Em pty	Empty
Y	6	Beginning of the year or enrollment date (Example: 10/12/13)
Z	6	End of the year or withdrawal date (Example 10/12/14)
AA	1	State Math Score Counts Y=Yes Leave all other blank
AB	1	Federal Math Score Counts Y=Yes Leave all other blank
AC	1	State Reading Score Counts Y=Yes Leave all other blank
AD	1	Federal Reading Score Counts Y=Yes Leave all other blank
AE	1	State Writing Score Counts Y=Yes Leave all other blank
AF	1	State Science Score Counts Y=Yes Leave all other blank
AG	1	LEP Status Y=Yes Leave all other blank
AH	2	Number of years in US Schools
AI	1	Bilingual Program

		Y=Yes
		Leave all other blank
AJ	1	LEP Parent Denial
		Y=Yes
		Leave all other blank
AK	1	Attends after school tutoring
		Y=Yes
		Leave all other blank
AL	1	Participated in Math Intervention Year 1
		Y=Yes
		Leave all other blank
AM	1	Participated in Math Intervention Year 2
		Y=Yes
		Leave all other blank
AN	1	Participated in Math Intervention Year 3
		Y=Yes
		Leave all other blank
AO	1	Participated in Reading Intervention Year 1
		Y=Yes
		Leave all other blank
AP	1	Participated in Reading Intervention Year 2
		Y=Yes
		Leave all other blank
AQ	1	Participated in Reading Intervention Year 3
		Y=Yes
		Leave all other blank
AR	1	Speech
		Y=Yes
		Leave all other blank
AS	1	Dyslexia Reading Program (DRD)
		Y=Yes
		Leave all other blank
AT	1	Gifted and Talented
		Y=Yes
		Leave all other blank
AU	1	Coded as Special Education
		Y=Yes
		Leave all other blank
AV	2	Special Education Setting Code
		41=Mainstream
		42=Resource
		00=Speech
AW	10	Recommended SPED Math Test School Year 1
		LAT Math
		TAK ALT
		TAKS
		TAKS A
		TAKS M
		Leave all others blank
AX	10	Recommended SPED or LEP Math Test Year 2
		LAT Math
		TAK ALT

		TAKS
		TAKS A
		TAKS M
		Leave all others blank
AY	10	Recommended SPED Reading Test Year 1
		LAT Math
		TAK ALT
		TAKS
		TAKS A
		TAKS M
		Leave all others blank
AZ	10	Recommended SPED or LEP Reading Test Year 2
		LAT Math
		TAK ALT
		TAKS
		TAKS A
		TAKS M
		Leave all others blank
BA	10	Recommended SPED Writing Test Year 1
		LAT Math
		TAK ALT
		TAKS
		TAKS A
		TAKS M
		Leave all others blank
BB	10	Recommended SPED or LEP Writing Year 2
		LAT Math
		TAK ALT
		TAKS
		TAKS A
		TAKS M
		Leave all others blank
BC	10	Recommended SPED Science Test Year 1
		LAT Math
		TAK ALT
		TAKS
		TAKS A
		TAKS M
		Leave all others blank
BD	10	Recommended SPED or LEP Science Test Year 2
		LAT Math
		TAK ALT
		TAKS
		TAKS A
		TAKS M
		Leave all others blank
BE	5	TELPAS: RPTE Reading Spring year
BF	5	TELPAS: RPTE Reading Proficiency Rate
BG	5	TELPAS: RPTE Scale Score Year 1
BH	5	TELPAS: RPTE Scale Score Year 2
BI	5	TELPAS: RPTE Reading Rating Year 2
BJ	5	TELPAS: RPTE Scale Score Year 3

BK	5	TELPAS: RPTE Reading Rating Year 3
BL	5	TELPAS Writing Spring Year 1
BM	5	TELPAS Writing Spring Year 2
BN	5	TELPAS Writing Spring Year 3
BO	5	TELPAS Writing Spring Year 4
BP	5	TELPAS Composite Rating Spring Year 1
BQ	5	TELPAS Composite Rating Spring Year 2
BR	5	TELPAS Composite Rating Spring Year 3
BS	5	TELPAS Composite Rating Year 4
BT	5	ORAL IPT EOY Year 1
BU	5	ORAL IPT EOY Year 2
BV	5	ORAL IPT EOY Year 3
BW	5	TELPAS Listening Year 1
BX	5	I Nova Goal
BY	3	I Nova Goal Indicator P=Pass ST= Special Target T= Target
BZ	3	INOVA Reading Intervention Scenario Current Year
CA	10	Reading Intervention Color Current Year
CB	10	Reading Bell Curve Current Year
CC	10	Predicted Current Year Reading Score
CD	6	TAKS Raw Score Year 1
CE	6	TAKS Scale Score Year 1
CF	6	TAKS Scale Score Year 1 Pass or Fail P=Pass F=Fail
CG	1	TAKS Testing Language Year 1 E=English S=Spanish
CH	2	TAKS Objective 1-15
CI	2	TAKS Objective 2-7
CJ	2	TAKS Objective 3-6
CK	2	TAKS Objective 4-8
CL	Em pty	Empty
CM	6	TAKS Raw Score Year 2
CN	6	TAKS Scale Score Year 2
CO	3	TAKS Percentage Year 2
CP	6	TAKS Scale Score Year 2 Pass or Fail P=Pass F=Fail
CQ	1	TAKS Testing Language Year 2 E=English S=Spanish
CR	2	TAKS Objective 1-15
CS	2	TAKS Objective 2-7
CT	2	TAKS Objective 3-6
CU	2	TAKS Objective 4-8
CV	1	2^{nd} Administration of TAKS test Y=Yes Leave all others blank

CW	5	Year 2 Vertical Scale Score
CX	5	Year 2 Lexile Measure
CY	5	Year 2 Texas Projected Measure Score
CZ	1	Student Counts as a TPM Pass Y=Yes Leave all others blank
DA	2	District Benchmark Reading #1
DB	1	Benchmark #1 Pass or Fail P=Pass F=Fail =IF(DA4>69,”P”,”F”)
DC	2	District Benchmark Reading #2
DD	1	Benchmark #2 Pass or Fail P=Pass F=Fail =IF(DC5>69,”P”,”F”)
DE	2	Mock #1 Raw Score Reading
DF	3	Mock #1 Vertical Scale Score Reading =LOOKUP(DE5,{0-36},{“71”-“794”})
DG	3	Mock #1 Percentages =DE4*2.77%
DH	1	Mock #1 Pass or Fail P=Pass F=Fail =IF(DE5>22,”P”,”F”)
DI	1	Mock #1 Testing Language E=English S=Spanish
DJ	6	Target Status =IF(DG4<46%, “target”,””)
DK	4	Based on Mock #1 R&M, Student TPM for 5th =253.26+(0.4042*DF4)+(0.2915*GG4)+(0.0559*583)
DL	1	Mock#1 R&M TPM Projected will Count Student as a Pass =IF(DK4>619,”P”,”F”)
DM	Em pty	Empty
DN	2	Mock #2 Raw Score
DO	3	Mock #2 Vertical Scale Score =LOOKUP(DN4,{0-36},{“71”-“794”})
DP	3	Mock #2 Percentages =DNR*0.0277
DQ	1	Mock #2 Pass or Fail =IF(DN$>22,”P”,”F”)
DR	1	Mock #2 Testing Language E=English S=Spanish
DS	6	Target Status =IF(DP4<56%,”target”,””)
DT	2	Value Added from Mock #1 to Mock #2 =DN4-DE4
DU	3	Based on Mock #2 R&M, Student TPM for 5th

		=172.76+(0.5066*DO4)+(0.2327*GP4)+(0.0893*583)
DV	1	Mock #2 R&M TPM Projected will Count Student as a Pass P=Pass F=Fail =IF(DU4>619,”P”,”F”)
DW	Empty	Empty
DX	Empty	Empty
DY	2	Mock # 3 Raw Score Reading
DZ	3	Mock #3 Vertical Scale Score Reading =LOOKUP (DY4,{0-36},{“71”-“794”})
EA	3	Mock #3 Percentages Reading =DY4*0.0277
EB	1	Mock #3 Pass or Fail Reading P=Pass F=Fail =IF(DY4>22,”P”,”F”)
EC	1	Mock #3 Testing Language Reading E=English S=Spanish
ED	6	Target Status Reading =IF(EA4<66%,”target”,””)
EE	2	# of Questions Needed to Pass Reading #23-DY4
EF	4	Based on Mock #3 R&M, Student TPM for 5^{th} Reading =172.76+(0.5066*DZ4)+(0.2327*GZ4)+(0.0893*583)
EG	Empty	Empty
EH	Empty	Empty
EI	2	TAKS Year 2 Raw Score
EJ	2	TAKS Year 2 Scale Score
EK	3	TAKS Year 2 Percentage
EL	2	TAKS Year 2 Pass or Fail P=Pass F=Fail
EM	1	TAKS Year 2 Testing Language E=English S=Spanish
EN	2	TAKS Year 2 Objective 1-15
EO	2	TAKS Year 2 Objective 2-7
EP	2	TAKS Year 2 Objective 3-6
EQ	2	TAKS Year 2 Objective 4-8
ER	2	# of question needed to pass (3rd = 23)(5^{th}=28)
ES	2	Value Added From Mock #1 to TAKS
ET	1	Second Administration Y=Yes Leave all others blank
EU	4	Student Reading TPM
EV	1	Based on TPM Student will count as a Pass Y=Yes

		Leave all others blank
EW	Empty	Empty
EX	3	I NOVA Goal Math
EY	3	INOVA Math Intervention Scenario Current Year
EZ	10	Math Intervention Color Current Year
FA	10	Math Bell Curve Current Year
FB	10	Predicted Current Year Math Score
FC	6	TAKS Math Scale Score Year 1
FD	6	TAKS Scale Score Year 1(2100)
FE	6	TAKS Scale Score Year 1 Pass or Fail
		P=Pass
		F=Fail
FF	1	TAKS Testing Language Year 1
		E=English
		S=Spanish
FG	2	TAKS Objective 1-15
FH	2	TAKS Objective 2-7
FI	2	TAKS Objective 3-6
FJ	2	TAKS Objective 4-8
FK	2	TAKS Objective 5-5
FL	2	TAKS Objective 6
FM	6	TAKS Raw Score Year 2 Math (2100)
FN	6	TAKS Scale Score Year 2 Pass or Fail
		P=Pass
		F=Fail
FO	3	TAKS Raw ScoreYear 2 (36)
FP	6	TAKS Testing Language Year 2
		E=English
		S=Spanish
FQ	1	TAKS Objective 1-15
FR	2	TAKS Objective 2-7
FS	2	TAKS Objective 3-6
FT	2	TAKS Objective 4-8
FU	2	TAKS Objective 5-5
FV	2	TAKS Objective 6
FW	5	Year 2 Vertical Scale Score
FX	5	Year 2 TPM Score
FY	1	Student Counts as a TPM Pass
		Y=Yes
		Leave all others blank
FZ	2	District Benchmark Math #1
GA	1	Benchmark #1 Pass or Fail
		P=Pass
		F=Fail
		=IF(DA4>69,”P”,”F”)
GB	1	Benchmark Math #1 Testing Language
		Y=Yes
		Leave all others blank
GC	2	District Benchmark Math #2
GD	1	Benchmark #2 Pass or Fail

		P=Pass
		F=Fail
		=IF(DC5>69,”P”,”F”)
GE	1	Benchmark #2 Pass or Fail
		Y=Yes
		Leave all others blank
GF	2	Mock #1 Raw Score Math
GG	3	Mock #1 Vertical Scale Score Math
		=LOOKUP(DE5,{0-36},{“71”-“794”})
GH	3	Mock #1 Percentages
		=DE4*2.77%
GI	1	Mock #1 Pass or Fail
		P=Pass
		F=Fail
		=IF(DE5>22,”P”,”F”)
GJ	6	Target Status
		=IF(DG4<46%, “target”,””)
GK	1	Mock #1 Testing Language
		E=English
		S=Spanish
GL	4	Based on Mock #1 R&M, Student TPM for 5th
		=253.26+(0.4042*DF4)+(0.2915*GG4)+(0.0559*583)
GM	1	Mock#1 R&M TPM Projected will Count Student as a Pass
		=IF(DK4>619,”P”,”F”)
GN	Em pty	Empty
GO	2	Mock #2 Raw Score
GP	3	Mock #2 Scale Score
		=LOOKUP(GO4,{0-42},{“156”-“836”})
GQ	3	Mock #2 Percentages
		=GO4*0.0238
GR	1	Mock #2 Pass or Fail
		=IF(GO4>27,”P”,”F”)
GS	6	Target Status
		=IF(GQ4<56%,”target”,””)
GT	1	Mock #2 Testing Language
		E=English
		S=Spanish
GU	2	Value Added from Mock #1 to Mock #2
		=GO4-GF4
GV	3	Based on Mock #2 R&M, Student TPM for 5th
		=224.78+(0.1904*DO4)+(0.2327*GP4)+(0.0589*598)
GW	1	Mock #2 R&M TPM Projected will Count Student as a Pass
		P=Pass
		F=Fail
		=IF(GV4>602,”P”,”F”)
GX	Em pty	Empty
GY	2	Mock # 3 Raw Score Math
GZ	3	Mock #3 Vertical Scale Score Reading
		=LOOKUP (gY4,{0-40},{“99”-“777”})
HA	3	Mock #3 Percentages Math

		=GY4*0.025
HB	1	Mock #3 Pass or Fail Math P=Pass F=Fail =IF(GY4>22,"P","F")
HC	6	Target Status Math =IF(HA4<66%,"target","")
HD	1	Mock #3 Testing Language Math E=English S=Spanish
HE	2	# of Questions Needed to Pass Reading #23-GY4
HF	4	Based on Mock #3 R&M, Student TPM for 5th Reading =224.78+(0.1904*DZ4)+(0.6032*GZ4)+(0.0589*537)
HG	1	Mock #3 R&M TPM will count as a Pass P=Pass F=Fail
HH	Em pty	Empty
HI	4	TAKS Year 2 Math Scale (2100)
HJ	2	TAKS Year 2 Raw Score (36)
HK	2	TAKS Year 2 Pass or Fail P=Pass F=Fail
HL	1	TAKS Year 2 Testing Language E=English S=Spanish
HM	2	TAKS Year 2 Objective 1-15
HN	2	TAKS Year 2 Objective 2-7
HO	2	TAKS Year 2 Objective 3-6
HP	2	TAKS Year 2 Objective 4-8
HQ	2	TAKS Year 2 Objective 5-5
HR	2	TAKS Year 2 Objective 6
HS	4	TAKS Student Reading TPM
HT	1	Based on TPM Student will count as a Pass Y=Yes Leave all others blank
HU	2	# of Questions Needed to Pass
HV	2	Value Added From Mock #1 to TAKS
HW	4	TAKS Math Retake
HX	1	Benchmark Science #1 Pass or Fail P=Pas F=Fail
HY	1	Benchmark Science #1 Testing Language E=English S=Spanish
HZ	4	Benchmark Science #2
IA	1	Benchmark Science #2 Pass or Fail P=Pas F=Fail
IB	Em pty	Empty

IC	2	Mock#1 Science Raw Score Science
ID	4	Mock #1 Science Scale Score =LOOKUP(IC4({0-40}{“908”-“2787”})
IE	3	Mock #1 Science Percentage =IC4*0.025
IF	1	Mock #1 Pass or Fail P=Pass F=Fail =IF(IC4>29,”P”,”F”)
IG	6	Mock Science #1 Target Status =IF(IE4<46%,”target”,””)
IH	1	Mock #1 Science Testing Language E=English S=Spanish
II	3	Based on Mock #1 R,M, &S Student TPM =667.35+(0.5427*DF4)+(0.6618*GG4)+(0.4054*ID4)+(0.0707*2144)
IJ	1	Student TPM will Count as a Pass P=Pass F=Fail
IK	Em pty	Empty
IL	2	Mock#2 Science Raw Score Science
IM	4	Mock #2 Science Scale Score =LOOKUP(IL4({0-40}{“908”-“2787”})
IN	3	Mock #1 Science Percentage =IL4*0.025
IO	1	Mock #2 Pass or Fail P=Pass F=Fail =IF(IL4>29,”P”,”F”)
IP	6	Mock Science #1 Target Status =IF(IL4<46%,”target”,””)
IQ	1	Mock #2 Science Testing Language E=English S=Spanish
IR	2	Value Added from Mock #1 to Mock #2 IL4-IC4
IS	3	Based on Mock #2 R,M, &S Student TPM =667.35+(0.5427*DO4)+(0.6618*GP4)+(0.4054*IM4)+(0.0707*2144)
IT	1	Student TPM will Count as a Pass P=Pass F=Fail =IF(IS4>2099,”P”,”F”)
IU	Em pty	Empty
IV	2	Mock#3 Science Raw Score Science
IW	4	Mock #3 Science Scale Score =LOOKUP(IV4({0-40}{“908”-“2787”})
IX	3	Mock #1 Science Percentage =IV4*0.025
IY	1	Mock #2 Pass or Fail P=Pass

		F=Fail
		=IF(IV4>29,”P”,”F”)
IZ	6	Mock Science #1 Target Status
		=IF(IV4<46%,”target”,””)
JA	1	Mock #2 Science Testing Language
		E=English
		S=Spanish
JB	2	Value Added from Mock #1 to Mock #2
		=30-IV4
JC	3	Based on Mock #2 R,M, &S Student TPM
		=667.35+(0.5427*DZ4)+(0.6618*GZ4)+(0.4054*IW4)+(0.0707*2144)
JD	1	Student TPM will Count as a Pass
		P=Pass
		F=Fail
		=IF(jc4>2099,”P”,”F”)
JE	2	Value Added From Mock 1 to Mock 3
		=IV4-IC4
JF	Em pty	Empty
JG	2	TAKS Year 2 Raw Score Science
JH	4	TAKS Year 2 Scale Score
JI	2	TAKS Year 2 Pass or Fail
		P=Pass
		F=Fail
JJ	2	Science Objective 1-15
JK	2	Science Objective 2-7
JL	2	Science Objective 3-6
JM	2	Science Objective 4-8
JN	4	Student TPM Score
JO	1	Student Counts as a Pass with TPM
JP	Em pty	Empty
JQ	4	I NOVA Writing Goal
JR	2	Benchmark Writing #1
JS	1	Benchmark #1 Pass or Fail
		P=Pass
		F=Fail
JT	1	Benchmark #1 Testing Language
		E=English
		S=Spanish
JU	2	Benchmark #2
JV	1	Benchmark #2 Pass or Fail
		P=Pass
		F=Fail
JW	1	Benchmark #2 Testing Language
		E=English
		S=Spanish
JX	Em pty	Empty
JY	2	Mock #1 Percentage Writing
		KB4*0.0277
JZ	2	Mock Writing #1 Prompt Score

KA	2	Mock Writing #1 Raw Score
KB	3	Prompt + Raw Score
KC	4	Mock #1 Scale Score
KD	1	Mock Writing #1 Pass or Fail P=Pass F=Fail
KE	4	Based on Mock #1 RWM, Student TPM for Writing =1140+(0.4581*DF4)+(0.3568*GG4)+(0.2997*KC4)+(0.002*2231)
KF	1	RMW TPM will count as a Pass =IF(KE4>2099,"P","F")
KG	Em pty	Empty
KH	2	Mock #2 Percentage Writing KK4*0.0277
KI	2	Mock Writing #2 Prompt Score
KJ	2	Mock Writing #2 Raw Score
KK	3	Prompt + Raw Score
KL	4	Mock #2 Scale Score =LOOKUP(KK4,{0-32},{"1465"-"3021"})
KM	1	Mock Writing #2 Pass or Fail P=Pass F=Fail
KN	2	Value Added from Mock #1 to Mock #2 =KK4-KB4
KO	4	Based on Mock #2 RWM, Student TPM for Writing =1140+(0.4581*DF4)+(0.3568*GG4)+(0.2997*KC4)+(0.002*2231)
KP	1	RMW TPM will count as a Pass =IF(KE4>2099,"P","F")
KQ	Em pty	Empty
KR	2	Mock #3 Percentage Writing KK4*0.0277
KS	2	Mock Writing #3 Prompt Score
KT	2	Mock Writing #3 Raw Score
KU	3	Prompt + Raw Score
KV	4	Mock #3 Scale Score =LOOKUP(KU4,{0-32},{"1465"-"3021"})
KW	1	Mock Writing #3 Pass or Fail P=Pass F=Fail
KX	2	Value Added from Mock #1 to Mock #3 =KU4-KB4
KY	4	Based on Mock #2 RWM, Student TPM for Writing =1140+(0.4581*DZ4)+(0.3568*GZ4)+(0.2997*KV4)+(0.002*2231)
KZ	1	RMW TPM will count as a Pass =IF(KY4>2099,"P","F")
LA	2	# of Questions Needed to Pass =17-KT4
LB	Em pty	Empty
LC	4	I NOVA Writing Goal
LD	4	TAKS Year 2 Writing

LE	1	TAKS Year 2 Pass or Fail P=Pass F=Fail
LF	2	TAKS Year 2 Raw Score
LG	1	TAKS Year 2 Testing Language E=English S=Spanish
LH	2	TAKS Objective 1 & 2 - Prompt
LI	2	Objective 3
LJ	2	Objective 4
LK	2	Objective 5
LL	2	Objective 6
LM	3	Student Writing TPM
LN	1	Student Courts as a Pass with TPM
LO	3	Intervention Weekly Reading Assessment #1
LP	3	Intervention Weekly Reading Assessment #2
LQ	3	Intervention Weekly Reading Assessment #3
LR	3	Intervention Weekly Reading Assessment #4
LS	3	Intervention Weekly Reading Assessment #5
LT	3	Intervention Weekly Reading Assessment #6
LU	3	Intervention Weekly Reading Assessment #7
LV	3	Intervention Weekly Reading Assessment #8
LW	3	Intervention Weekly Reading Assessment #9
LX	3	Intervention Weekly Reading Assessment #10
LY	3	Intervention Weekly Reading Assessment #11
LZ	3	Intervention Weekly Reading Assessment #12
MA	3	Intervention Weekly Reading Assessment #13
MB	3	Intervention Weekly Reading Assessment #14
MC	3	Intervention Weekly Reading Assessment #15
MD	3	Intervention Weekly Reading Assessment #16
ME	3	Intervention Weekly Reading Assessment #17
MF	3	Intervention Weekly Reading Assessment #18
MG	3	Intervention Weekly Reading Assessment #19
MH	3	Intervention Weekly Reading Assessment #20
MI	3	Intervention Weekly Math Assessment #1
MJ	3	Intervention Weekly Math Assessment #2
MK	3	Intervention Weekly Math Assessment #3
ML	3	Intervention Weekly Math Assessment #4
MM	3	Intervention Weekly Math Assessment #5
MN	3	Intervention Weekly Math Assessment #6
MO	3	Intervention Weekly Math Assessment #7
MP	3	Intervention Weekly Math Assessment #8
MQ	3	Intervention Weekly Math Assessment #9
MR	3	Intervention Weekly Math Assessment #10
MS	3	Intervention Weekly Math Assessment #11
MT	3	Intervention Weekly Math Assessment #12
MU	3	Intervention Weekly Math Assessment #13
MV	3	Intervention Weekly Math Assessment #14
MW	3	Intervention Weekly Math Assessment #15
MX	3	Intervention Weekly Math Assessment #16
MY	3	Intervention Weekly Math Assessment #17
MZ	3	Intervention Weekly Math Assessment #18

NA	3	Intervention Weekly Math Assessment #19
NB	3	Intervention Weekly Math Assessment #20
NC	3	Intervention Weekly Science Assessment #1
ND	3	Intervention Weekly Science Assessment #1
NE	3	Intervention Weekly Science Assessment #2
NF	3	Intervention Weekly Science Assessment #3
NG	3	Intervention Weekly Science Assessment #4
NH	3	Intervention Weekly Science Assessment #5
NI	3	Intervention Weekly Science Assessment #6
NJ	3	Intervention Weekly Science Assessment #7
NK	3	Intervention Weekly Science Assessment #8
NL	3	Intervention Weekly Science Assessment #9
NM	3	Intervention Weekly Science Assessment #10
NN	3	Intervention Weekly Science Assessment #11
NO	3	Intervention Weekly Science Assessment #12
NP	3	Intervention Weekly Science Assessment #13
NQ	3	Intervention Weekly Science Assessment #14
NR	3	Intervention Weekly Science Assessment #15
NS	3	Intervention Weekly Science Assessment #16
NT	3	Intervention Weekly Science Assessment #17
NU	3	Intervention Weekly Science Assessment #18
NV	3	Intervention Weekly Science Assessment #19
NW	3	Intervention Weekly Science Assessment #20
NX	3	Intervention Weekly Writing Assessment #1
NY	3	Intervention Weekly Writing Assessment #2
NZ	3	Intervention Weekly Writing Assessment #3
OA	3	Intervention Weekly Writing Assessment #4
OB	3	Intervention Weekly Writing Assessment #5
OC	3	Intervention Weekly Writing Assessment #6
OD	3	Intervention Weekly Writing Assessment #7
OE	3	Intervention Weekly Writing Assessment #8
OF	3	Intervention Weekly Writing Assessment #9
OG	3	Intervention Weekly Writing Assessment #10
OH	3	Intervention Weekly Writing Assessment #11
OI	3	Intervention Weekly Writing Assessment #12
OJ	3	Intervention Weekly Writing Assessment #13
OK	3	Intervention Weekly Writing Assessment #14
OL	3	Intervention Weekly Writing Assessment #15
OM	3	Intervention Weekly Writing Assessment #16
ON	3	Intervention Weekly Writing Assessment #17
OO	3	Intervention Weekly Writing Assessment #18
OP	3	Intervention Weekly Writing Assessment #19
OQ	3	Intervention Weekly Writing Assessment #20
OR-PB	Empty	Empty
PC	2	Section of Teacher/grade level (Example: 4E, 3B, 5A)
PD	Empty	Empty
PE	3	Total # of Students (F) TAKS Year 1
PF	3	Total # Students Who Count (F & AA) =COUNTIF(F:$F183,"5A")
PG	3	Total # Students Who Count Who Passed (F & AA & CG)

		=SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
PH	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
PI	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
PJ	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
PK	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
PL	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
PM	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
PN	Em pty	Empty
PO	3	Total # of Students (F) Year 2 TAKS
PP	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
PQ	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
PR	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
PS	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
PT	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
PU	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
PV	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
PW	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
PX	Em pty	Empty
PY	3	Total # of Students (F) Reading Mock TAKS #1
PZ	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
QA	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
QB	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
QC	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
QD	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
QE	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
QF	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
QG	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
QH	Em	Empty

	pty	
QI	3	Total # of Students (F) Reading Benchmark #1
QJ	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
QK	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
QL	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
QM	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
QN	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
QO	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
QP	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
QQ	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
QR	Em pty	Empty
QS	3	Total # of Students (F) Reading Mock TAKS #2
QT	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
QU	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
QV	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
QW	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
QX	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
QY	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
QZ	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
RA	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
RB	Em pty	Empty
RC	3	Total # of Students (F) Reading Benchmark #2
RD	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
RE	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
RF	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
RG	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
RH	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
RI	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26

RJ	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
RK	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
RL	Empty	Empty
RM	3	Total # of Students (F) Reading Mock #3
RN	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
RO	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
RP	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
RQ	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
RR	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
RS	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
RT	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
RU	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
RV	Empty	Empty
RW	3	Total # of Students (F) Current Year TAKS Reading
RX	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
RY	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
RZ	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
SA	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
SB	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
SC	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
SD	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
SE	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
SF-SH	Empty	Empty
SI	2	Grade Level Section/Grade
SJ	Empty	Empty
SK	3	Total # of Students (F) Year 1 TAKS Math
SL	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
SM	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))

SN	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
SO	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
SP	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
SQ	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
SR	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
SS	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
ST	Empty	Empty
SU	3	Total # of Students (F) Year 2TAKS Math
SV	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
SW	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
SX	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
SY	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
SZ	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
TA	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
TB	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
TC	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
TD	Empty	Empty
TE	3	Total # of Students (F) Math Mock TAKS #1
TF	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
TG	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
TH	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
TI	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
TJ	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
TK	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
TL	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
TM	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
TN	Empty	Empty

TO	3	Total # of Students (F) Math Benchmark #1
TP	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,"5B")
TQ	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383="A")*($AC4:$AC383="Y")))
TR	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183"5D")*($DH4:$DH183="P")))
TS	3	Total Students in Grade Level =IF(PE24=0,"",PG24/PE24)
TT	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
TU	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
TV	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
TW	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
TX	Empty	Empty
TY	3	Total # of Students (F) Math Mock TAKS #2
TZ	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,"5B")
UA	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383="A")*($AC4:$AC383="Y")))
UB	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183"5D")*($DH4:$DH183="P")))
UC	3	Total Students in Grade Level =IF(PE24=0,"",PG24/PE24)
UD	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
UE	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
UF	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
UG	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
UH	Empty	Empty
UI	3	Total # of Students (F) Math Benchmark #2
UJ	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,"5B")
UK	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383="A")*($AC4:$AC383="Y")))
UL	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183"5D")*($DH4:$DH183="P")))
UM	3	Total Students in Grade Level =IF(PE24=0,"",PG24/PE24)
UN	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
UO	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
UP	3	Passing Rate for Grade Level

		PG21+PG22+PG23+PG24+PG25+PG26
UQ	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
UR	Empty	Empty
US	3	Total # of Students (F) Math Mock TAKS #3
UT	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
UU	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
UV	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
UW	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
UX	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
UY	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
UZ	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
VA	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
VB	Empty	Empty
VC	3	Total # of Students (F) Current Year TAKS Math
VD	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
VE	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
VF	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
VG	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
VH	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
VI	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
VJ	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
VK	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
VL-VY	Empty	Empty
VX	30	Listing:
73		Sub Groups
75		Hispanic
77		Economically Disadvantaged (w=Y)
78		All Students
85		Hispanic (x=H)
88		All Students
VY	2	Section of grade level and teacher
VZ	Em	Empty

	pty	
WA	3	Total # of Students (F) TAKS Writing/Science
WB	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,"5B")
WC	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383="A")*($AC4:$AC383="Y")))
WD	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183"5D")*($DH4:$DH183="P")))
WE	3	Total Students in Grade Level =IF(PE24=0,"",PG24/PE24)
WF	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
WG	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
WH	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
WI	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
WJ	Em pty	Empty
WK	3	Total # of Students (F) Writing/Science Benchmark #1
WL	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,"5B")
WM	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383="A")*($AC4:$AC383="Y")))
WN	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183"5D")*($DH4:$DH183="P")))
WO	3	Total Students in Grade Level =IF(PE24=0,"",PG24/PE24)
WP	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
WQ	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
WR	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
WS	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
WT	Em pty	Empty
WU	3	Total # of Students (F) Writing/Science Mock TAKS #2
WV	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,"5B")
WW	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383="A")*($AC4:$AC383="Y")))
WX	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183"5D")*($DH4:$DH183="P")))
WY	3	Total Students in Grade Level =IF(PE24=0,"",PG24/PE24)
WZ	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
XA	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26

XB	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
XC	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
XD	Em pty	Empty
XE	3	Total # of Students (F) Writing/Science Benchmark #2
XF	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,"5B")
XG	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383="A")*($AC4:$AC383="Y")))
XH	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183"5D")*($DH4:$DH183="P")))
XI	3	Total Students in Grade Level =IF(PE24=0,"",PG24/PE24)
XJ	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
XK	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
XL	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
XM	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
XN	Em pty	Empty
XO	3	Total # of Students (F) Writing/Science Mock #3
XP	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,"5B")
XQ	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383="A")*($AC4:$AC383="Y")))
XR	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183"5D")*($DH4:$DH183="P")))
XS	3	Total Students in Grade Level =IF(PE24=0,"",PG24/PE24)
XT	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
XU	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
XV	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
XW	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
XX	Em pty	Empty
XY	3	Total # of Students (F) TAKS Current Year Writing/Science
XZ	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,"5B")
YA	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383="A")*($AC4:$AC383="Y")))
YB	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183"5D")*($DH4:$DH183="P")))
YC	3	Total Students in Grade Level

		=IF(PE24=0,””,PG24/PE24)
YD	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
YE	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
YF	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
YG	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
YH-YQ	Empty	Empty
YR	2	Section of grade level and teacher
YS	Empty	Empty
YT	3	Total # of Students (F) TAKS Current Year TAKS Reading (AYP)
YU	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
YV	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
YW	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
YX	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
YY	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
YZ	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
ZA	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
ZB	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
ZC	Empty	Empty
ZD	3	Total # of Students (F) TAKS Year 2 TAKS Reading (AYP)
ZE	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
ZF	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
ZG	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
ZH	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
ZI	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
ZJ	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
ZK	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
ZL	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
ZM	Empty	Empty

ZN	3	Total # of Students (F) TAKS Mock TAKS #1 Reading (AYP)
ZO	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
ZP	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
ZQ	2	Passing Rate by Homeroom =SUMPRODUCT(((F:$F183”5D”)*($DH4:$DH183=”P”)))
ZR	3	Total Students in Grade Level =IF(PE24=0,””,PG24/PE24)
ZS	3	Total Students in Grade Level Who Count =PE21+PE22+PE23+PE24+PE25+PE26
ZT	3	Total # Students in Grade Level Who Count Who Passed = PF21+PF22+PF23+PF24+PF25+PF26
ZU	3	Passing Rate for Grade Level PG21+PG22+PG23+PG24+PG25+PG26
ZV	3	Passing Rate for the Campus =(PK21+PK13)/(PK21+PK13)
ZW	Em pty	Empty
ZX	3	Total # of Students (F) TAKS Benchmark Reading (AYP)
ZY	3	Total # Students Who Count (F & AA) =COUNTIF($F4:$F176,”5B”)
ZZ	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((V:$V383=”A”)*($AC4:$AC383=”Y”)))
AAA	2	Passing Rate by Homeroom =IF(ZY4=0,””,ZZ4/ZY4)
AAB	3	Total Students in Grade Level =ZX4+ZX5+ZX6+ZX7+ZX8+ZX9
AAC	3	Total Students in Grade Level Who Count = ZY4+ZY5+ZY6+ZY7+ZY8+ZY9
AAD	3	Total # Students in Grade Level Who Count Who Passed = ZZ4+ZZ5+ZZ6+ZZ7+ZZ8+ZZ9
AAE	3	Passing Rate for Grade Level = IF(AAC4=0,””,AAD4/AAC4)
AAF	3	Passing Rate for the Campus =(AAD41+AD13)/(AAC4+AAC13+AAC21)
AAG	Em pty	Empty
AAH	3	Total # of Students (F) TAKS Mock TAKS #2 Reading (AYP) =COUNTIF($F4:$F176,”3A”)
AAI	3	Total # Students Who Count (F & AA) =SUMPRODUCT(((F:$F383=”3A”)*($AD4:$AD176=”Y”)))
AAJ	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((F:$F176=”3B”)*($AD4:$AD176=”P”)))
AAK	2	Passing Rate by Homeroom =IF(AA24=0,””,AAJ5/AAJ5)
AAL	3	Total Students in Grade Level =AAH4+AAH5+ AAH6+ AAH7+ AAH8+ AAH9
AAM	3	Total Students in Grade Level Who Count =AAI4+AAI5+ AAI6+ AAI7+ AAI8+ AAI9
AAN	3	Total # Students in Grade Level Who Count Who Passed =AAJ4+AAJ5+ AAJ6+ AAJ7+ AAJ8+ AAJ9

AAO	3	Passing Rate for Grade Level =IF(AAM4=0,””,AAN4/AAM4)
AAP	3	Passing Rate for the Campus =(AAN4+AAN21+AAN13)/(AAM4+AAM21+AAM13)
AAQ	Em pty	Empty
AAR	3	Total # of Students (F) TAKS Benchmark #2 Reading (AYP) =COUNTIF($F4:$F176,”3A”)
AAS	3	Total # Students Who Count (F & AA) =SUMPRODUCT(((F:$F176=”A”)*($AD4:$AD176=”Y”)))
AAT	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT(((F:$F176=”3A”)*($AD4:$AD176=”Y”)*($DD4:$DD 176=”P”)))
AAU	2	Passing Rate by Homeroom =IF(AAS4=0,””,AAT4/AAS4)
AAV	3	Total Students in Grade Level =AAR4+AAR5+AAR6+AAR7+AAR8+AAR9
AAW	3	Total Students in Grade Level Who Count =AAS4+AAS5+AAS6+AAS7+AAS8+AAS9
AAX	3	Total # Students in Grade Level Who Count Who Passed =AAT4+AAT5+AAT6+AAT7+AAT8+AAT9
AAY	3	Passing Rate for Grade Level =IF(AAW4=0,AAX4/AAW4)
AAZ	3	Passing Rate for the Campus =(AAX4+ AAX 21+ AAX 13)/(AAW4+AAW21+AAW13)
ABA	Em pty	Empty
ABB	3	Total # of Students (F) TAKS Mock TAKS #3 Reading (AYP) =COUNTIF($F4:$F176,”3A”)
ABC	3	Total # Students Who Count (F & AA) =SUMPRODUCT(((F:$F176=”3A”)*($AD4:$AD176=”Y”)))
ABD	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT((($F4:$F176=”3A”)*($AD4:$AD176=”Y”)*($EB4:$EB1 76=”P”)))
ABE	2	Passing Rate by Homeroom =IF(ABC44=0,””,ABD4/ABC4)
ABF	3	Total Students in Grade Level =ABB4+ ABB5+ ABB6+ ABB7+ ABB8+ ABB9
ABG	3	Total Students in Grade Level Who Count =ABC4+ ABC5+ ABC6+ ABC7+ ABC8+ ABC9
ABH	3	Total # Students in Grade Level Who Count Who Passed =ABD4+ ABD5+ ABD6+ ABD7+ ABD8+ ABD9
ABI	3	Passing Rate for Grade Level =IF(ABG4=0,””,ABH4/ABG4)
ABJ	3	Passing Rate for the Campus =(ABH4+ABH21+ABH13)/(ABG4+BG21+ABG13)
ABK	Em pty	Empty
ABL	3	Total # of Students (F) TAKS Current Year TAKS Reading (AYP) =COUNTIF($4:$F176,”3A”)
ABM	3	Total # Students Who Count (F & AA) =SUMPRODUCT((($F4:$F176=”3A”)*($AD4:$AD176=”Y”)))

ABN	3	Total # Students Who Count Who Passed (F & AA & CG) =SUMPRODUCT((($F4:$F176=”3A”)*($AD4:$AD176=”Y”)*($EL4:$EL176=”P”)))
ABO	2	Passing Rate by Homeroom =IF(ABM4=0,””,ABN4/ABM4)
ABP	3	Total Students in Grade Level =ABL4+ ABL5+ ABL6+ ABL7+ ABL8+ ABL9
ABQ	3	Total Students in Grade Level Who Count =ABM4+ ABM5+ ABM6+ ABM7+ ABM8+ ABM9
ABR	3	Total # Students in Grade Level Who Count Who Passed =ABN4+ ABN5+ ABN6+ ABN7+ ABN8+ ABN9
ABS	3	Passing Rate for Grade Level =IF(ABQ4=0,””,ABR4/ABQ4)
ABT	3	Passing Rate for the Campus =(ABR4+ABR13+ABR21)/(ABQ4+ABQ13+ABQ21)
ABU-ABX	Empty	Empty
ABY	30	Listing:
34		African American (V=AA)
39		LEP (AC=Y)
41		1st Year LEP Exit (AC = E1)
42		2nd Year LEP Exit (AC = E2)
45		LEP Parent Denials (AF =Y)
47		SPED TAKS (AU – 07-08) (AV -08-09)
48		SPED TAKS A (AU – 07-08) (AV -08-09)
49		SPED TAKS M (AU – 07-08) (AV -08-09)
ABZ	2	Section grade level by teacher
ABX-ACA	Empty	Empty
ACB	2	Total # of Students (F) 1st year TAKS Math
34		=COUNTIF($V4:$V383,"AA")
39		=COUNTIF($AG4:$AG383,"Y")
41		=COUNTIF($AG4:$AG383,"E1")
42		=SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y")))
45		=SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y")))
47		=SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS")))
48		=SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS A")))
49		=SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS M")))
ACD	2	Total # Students Who Count (F & AB) =SUMPRODUCT((($V4:$V383="AA")*($AB4:$AB383="Y")))
ACE	1	Passing Rate by Homeroom =IF(ACC34<=ACE29,"No","Yes")
ACF	3	Total Students in Grade Level =IF(ACC34<=200,"No","Yes")
ACG	3	Total Students in Grade Level Who Count
ACH	3	Total # Students in Grade Level Who Count Who Passed =SUMPRODUCT((($V4:$V383="AA")*($AB4:$AB383="Y")*($FD4:$FD383="P"))) =SUMPRODUCT((($AG4:$AG383="Y")*($AB4:$AB383="Y")*($FD4:$F

		D383="P"))) =SUMPRODUCT((($AG4:$AG383="E1")*($AB4:$AB383="Y")*($FD4:$FD383="P"))) =SUMPRODUCT((($AG4:$AG383="E2")*($AB4:$AB383="Y")*($FD4:$FD383="P"))) =SUMPRODUCT((($AJ4:$AJ383="Y")*($AB4:$AB383="Y")*($FD4:$FD383="P")))
ACI	3	Passing Rate for Grade Level =IF(ACC34=0,"",ACH34/ACC34) =IF(ACC39=0,"",ACH39/ACC39) =IF(ACC42=0,"",ACH42/ACC42) =IF(ACC45=0,"",ACH45/ACC45)
ACJ	3	Passing Rate for the Campus =IF(ACI34<67%,"NO","YES") =IF(ACI39<67%,"NO","YES")
ACK	Empty	Empty
ACL	2	Total # of Students (F) 2nd Year TAKS Math =COUNTIF($V4:$V383,"AA") =COUNTIF($AG4:$AG383,"Y") =COUNTIF($AG4:$AG383,"E1") =SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y"))) =SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y"))) =SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS"))) =SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS A"))) =SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS M")))
ACM	2	Total # Students Who Count (F & AB) =SUMPRODUCT((($V4:$V383="AA")*($AB4:$AB383="Y"))) =SUMPRODUCT((($AG4:$AG383="Y")*($AB4:$AB383="Y"))) =SUMPRODUCT((($AG4:$AG383="E2")*($AB4:$AB383="Y"))) =SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS")*($AB4:$AB383="Y"))) =SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS M")*($AB4:$AB383="Y")))
ACN	1	Total # Students Who Count Who Passed (F &AB & FI) =IF(ACM34<=50,"No","Yes") =IF(ACM39<=50,"No","Yes")
ACO	3	Passing Rate by Homeroom =IF(ACM34<=ACO29,"No","Yes") =IF(ACM39<=ACO27,"No","Yes")
ACP	3	Total Students in Grade Level =IF(ACM34<=200,"No","Yes") =IF(ACM39<=200,"No","Yes")
ACQ	3	Total Students in Grade Level Who Count =ACM13+ACM14+ACM15+ACM16+ACM17+ACM18
ACR	3	Total # Students in Grade Level Who Count Who Passed =ACN13+ACN14+ACN15+ACN16+ACN17+ACN18 =SUMPRODUCT((($V4:$V383="AA")*($AB4:$AB383="Y")*($FN4:$FN383="P"))) =SUMPRODUCT((($AG4:$AG383="E1")*($AB4:$AB383="Y")*($FN4:$FN383="P")))

		=SUMPRODUCT((($AJ4:$AJ383="Y")*($AB4:$AB383="Y")*($FN4:$FN383="P")))
		=SUMPRODUCT(((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS A")*($AB4:$AB383="Y")*($FN4:$FN383="P"))))
ACS	3	Passing Rate for Grade Level
		=IF(ACQ13=0,"",ACR13/ACQ13)
ACT	3	Passing Rate for Campus
		=(ACR21+ACR13)/(ACQ21+ACQ13)
		=IF(ACS34<67%,"NO","YES")
ACU	Empty	Empty
ACV	2	Total # of Students (F) Mock #1 TAKS Math
		=(ACR21+ACR13)/(ACQ21+ACQ13)
		=COUNTIF($V4:$V383,"AA")
		=COUNTIF($AG4:$AG383,"Y")
		=COUNTIF($AG4:$AG383,"E1")
		=SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y")))
		=SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y")))
		=SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS")))
		=SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS A")))
		=SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS M")))
ACW	2	Total # Students Who Count (F & AB)
		=SUMPRODUCT((($F4:$F176="3C")*($AB4:$AB176="Y")))
		=SUMPRODUCT((($F4:$F176="3F")*($AB4:$AB176="Y")))
		=SUMPRODUCT((($F4:$F176="4A")*($AB4:$AB176="Y")))
		=SUMPRODUCT((($V4:$V383="AA")*($AB4:$AB383="Y")))
		=SUMPRODUCT((($AG4:$AG383="E1")*($AB4:$AB383="Y")))
		=SUMPRODUCT((($AJ4:$AJ383="Y")*($AB4:$AB383="Y")))
		=SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS A")*($AB4:$AB383="Y")))
ACX	1	Total # Students Who Count Who Passed (F &AB & FI)
		=SUMPRODUCT((($F4:$F176="3C")*($AB4:$AB176="Y")*($GI4:$GI176="P")))
		=SUMPRODUCT((($F4:$F176="3F")*($AB4:$AB176="Y")*($GI4:$GI176="P")))
		=SUMPRODUCT((($F4:$F176="4A")*($AB4:$AB176="Y")*($GI4:$GI176="P")))
		=IF(ACW34<=50,"No","Yes")
		=IF(ACW39<=50,"No","Yes")
ACY	3	Passing Rate by Homeroom
		=IF(ACW6=0,"",ACX6/ACW6)
		=IF(ACW13=0,"",ACX13/ACW13)
		=IF(ACW34<=ACY29,"No","Yes")
		=IF(ACW39<=ACY27,"No","Yes")
ACZ	3	Total Students in Grade Level
		=ACV4+ACV5+ACV6+ACV7+ACV8+ACV9
		=ACV13+ACV14+ACV15+ACV16+ACV17+ACV18
		=IF(ACW34<=200,"No","Yes")
		=IF(ACW39<=200,"No","Yes")

ADA	3	Total Students in Grade Level Who Count
		=ACW4+ACW5+ACW6+ACW7+ACW8+ACW9
		=ACW13+ACW14+ACW15+ACW16+ACW17+ACW18
ADB	3	Total # Students in Grade Level Who Count Who Passed
		=ACX4+ACX5+ACX6+ACX7+ACX8+ACX9
		=ACX13+ACX14+ACX15+ACX16+ACX17+ACX18
		=SUMPRODUCT((($V4:$V383="AA")*($AB4:$AB383="Y")*($GI4:$GI383="P")))
		=SUMPRODUCT((($AG4:$AG383="Y")*($AB4:$AB383="Y")*($GI4:$GI383="P")))
		=SUMPRODUCT((($AG4:$AG383="E1")*($AB4:$AB383="Y")*($GI4:$GI383="P")))
		=SUMPRODUCT((($AG4:$AG383="E2")*($AB4:$AB383="Y")*($GI4:$GI383="P")))
		=SUMPRODUCT((($AJ4:$AJ383="Y")*($AB4:$AB383="Y")*($GI4:$GI383="P")))
		=SUMPRODUCT(((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS")*($AB4:$AB383="Y")*($GI4:$GI383="P"))))
		=SUMPRODUCT(((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS A")*($AB4:$AB383="Y")*($GI4:$GI383="P"))))
		=SUMPRODUCT(((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS M")*($AB4:$AB383="Y")*($GI4:$GI383="P"))))
ADC	3	Passing Rate for Grade Level
		=IF(ADA4=0,"",ADB4/ADA4)
		=IF(ADA13=0,"",ADB13/ADA13)
		=IF(ACW34=0,"",ADB34/ACW34)
		=IF(ACW39=0,"",ADB39/ACW39)
		=IF(ACW41=0,"",ADB41/ACW41)
		=IF(ACW42=0,"",ADB42/ACW42)
		=IF(ACW45=0,"",ADB45/ACW45)
		=IF(ACW47=0,"",ADB47/ACW47)
ADD	3	Passing Rate for Campus
		=(ADB4+ADB21+ADB13)/(ADA4+ADA21+ADA13)
		=IF(ADC34<67%,"NO","YES")
		=IF(ADC39<67%,"NO","YES")
ADE	Empty	Empty
ADF	2	Total # of Students (F) Math Benchmark #1 TAKS
		=COUNTIF($V4:$V383,"AA")
		=COUNTIF($AG4:$AG383,"Y")
		=COUNTIF($AG4:$AG383,"E1")
		=SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y")))
		=SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y")))
		=SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS")))
		=SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS A")))
		=SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS M")))
ADG	2	Total # Students Who Count (F & AB)
ADH	1	Total # Students Who Count Who Passed (F &AB & FI)
ADI	3	Passing Rate by Homeroom
ADJ	3	Total Students in Grade Level
ADK	3	Total Students in Grade Level Who Count
ADL	3	Total # Students in Grade Level Who Count Who Passed

ADM	3	Passing Rate for Grade Level
AND	3	Passing Rate for Campus
ADO	Empty	Empty
ADP	2	Total # of Students (F) Mock #2 Math =COUNTIF($V4:$V383,"AA") =COUNTIF($AG4:$AG383,"Y") =COUNTIF($AG4:$AG383,"E1") =SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y"))) =SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y"))) =SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS"))) =SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS A"))) =SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS M")))
ADQ	2	Total # Students Who Count (F & AB)
ADR	1	Total # Students Who Count Who Passed (F &AB & FI)
ADS	3	Passing Rate by Homeroom
ADT	3	Total Students in Grade Level
ADU	3	Total Students in Grade Level Who Count
ADV	3	Total # Students in Grade Level Who Count Who Passed
ADW	3	Passing Rate for Grade Level
ADX	3	Passing Rate for Campus
ADY	Empty	Empty
ADZ	2	Total # of Students (F) Benchmark #2 Math =COUNTIF($V4:$V383,"AA") =COUNTIF($AG4:$AG383,"Y") =COUNTIF($AG4:$AG383,"E1") =SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y"))) =SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y"))) =SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS"))) =SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS A"))) =SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS M")))
AEA	2	Total # Students Who Count (F & AB)
AEB	1	Total # Students Who Count Who Passed (F &AB & FI)
AEC	3	Passing Rate by Homeroom
AED	3	Total Students in Grade Level
AEE	3	Total Students in Grade Level Who Count
AEF	3	Total # Students in Grade Level Who Count Who Passed
AEG	3	Passing Rate for Grade Level
AEH	3	Passing Rate for Campus
AEI	Empty	Empty
AEJ	2	Total # of Students (F) Mock #3 Math =COUNTIF($V4:$V383,"AA") =COUNTIF($AG4:$AG383,"Y") =COUNTIF($AG4:$AG383,"E1") =SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y"))) =SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y"))) =SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS"))) =SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS A"))) =SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS M")))
AEK	2	Total # Students Who Count (F & AB)

AEL	1	Total # Students Who Count Who Passed (F &AB & FI)
AEM	3	Passing Rate by Homeroom
AEN	3	Total Students in Grade Level
AEO	3	Total Students in Grade Level Who Count
AEP	3	Total # Students in Grade Level Who Count Who Passed
AEQ	3	Passing Rate for Grade Level
AER	3	Passing Rate for Campus
AES	Empty	Empty
AET	2	Total # of Students (F) Current year TAKS Math
		=COUNTIF($V4:$V383,"AA")
		=COUNTIF($AG4:$AG383,"Y")
		=COUNTIF($AG4:$AG383,"E1")
		=SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y")))
		=SUMPRODUCT((($AG4:$AG383="Y")*($AJ4:$AJ383="Y")))
		=SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS")))
		=SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS A")))
		=SUMPRODUCT((($AU4:$AU383="Y")*($AZ4:$AZ383="TAKS M")))
AEU	2	Total # Students Who Count (F & AB)
		=SUMPRODUCT((($F4:$F176="3C")*($AB4:$AB176="Y")))
		=SUMPRODUCT((($F4:$F176="3F")*($AB4:$AB176="Y")))
		=SUMPRODUCT((($F4:$F176="4A")*($AB4:$AB176="Y")))
		=SUMPRODUCT((($V4:$V176="AA")*($AB4:$AB176="Y")))
		=SUMPRODUCT((($AG4:$AG176="Y")*($AB4:$AB176="Y")))
		=SUMPRODUCT((($AG4:$AG176="E1")*($AB4:$AB176="Y")))
		=SUMPRODUCT((($AG4:$AG176="E2")*($AB4:$AB176="Y")))
		=SUMPRODUCT((($AJ4:$AJ176="Y")*($AB4:$AB176="Y")))
		=SUMPRODUCT((($AU4:$AU176="Y")*($AZ4:$AZ176="TAKS")*($AB4:$AB176="Y")))
		=SUMPRODUCT((($AU4:$AU176="Y")*($AZ4:$AZ176="TAKS A")*($AB4:$AB176="Y")))
		=SUMPRODUCT((($AU4:$AU176="Y")*($AZ4:$AZ176="TAKS M")*($AB4:$AB176="Y")))
AEV	1	Total # Students Who Count Who Passed (F &AB & FI)
		=SUMPRODUCT((($F4:$F176="3C")*($AB4:$AB176="Y")*($HK4:$HK176="P")))
		=SUMPRODUCT((($F4:$F176="3F")*($AB4:$AB176="Y")*($HK4:$HK176="P")))
		=SUMPRODUCT((($F4:$F176="4A")*($AB4:$AB176="Y")*($HK4:$HK176="P")))
		=IF(AEU34<=50,"No","Yes")
		=IF(AEU39<=50,"No","Yes")
AEW	3	Passing Rate by Homeroom
		=IF(AEU6=0,"",AEV6/AEU6)
		=IF(AEU13=0,"",AEV13/AEU13)
		=IF(AEU34<=AEW29,"No","Yes")
		=IF(AEU39<=AEW27,"No","Yes")
AEX	3	Total Students in Grade Level
		=AET4+AET5+AET6+AET7+AET8+AET9
		=AET13+AET14+AET15+AET16+AET17+AET18
		=IF(AEU34<=200,"No","Yes")
		=IF(AEU39<=200,"No","Yes")

AEY	3	Total Students in Grade Level Who Count =AEU4+AEU5+AEU6+AEU7+AEU8+AEU9 =AEU13+AEU14+AEU15+AEU16+AEU17+AEU18
AEZ	3	Total # Students in Grade Level Who Count Who Passed =AEV4+AEV5+AEV6+AEV7+AEV8+AEV9 =AEV13+AEV14+AEV15+AEV16+AEV17+AEV18 =SUMPRODUCT((($V4:$V176="AA")*($AB4:$AB176="Y")*($HK4:$HK176="P"))) =SUMPRODUCT((($AG4:$AG176="Y")*($AB4:$AB176="Y")*($HK4:$HK176="P"))) =SUMPRODUCT((($AG4:$AG176="E1")*($AB4:$AB176="Y")*($HK4:$HK176="P"))) =SUMPRODUCT((($AG4:$AG176="E2")*($AB4:$AB176="Y")*($HK4:$HK176="P"))) =SUMPRODUCT((($AJ4:$AJ176="Y")*($AB4:$AB176="Y")*($HK4:$HK176="P"))) =SUMPRODUCT(((($AU4:$AU176="Y")*($AZ4:$AZ176="TAKS")*($AB4:$AB176="Y")*($HK4:$HK176="P")))) =SUMPRODUCT(((($AU4:$AU176="Y")*($AZ4:$AZ176="TAKS A")*($AB4:$AB176="Y")*($HK4:$HK176="P")))) =SUMPRODUCT(((($AU4:$AU176="Y")*($AZ4:$AZ176="TAKS M")*($AB4:$AB176="Y")*($HK4:$HK176="P"))))
AFA	3	Passing Rate for Grade Level =IF(AEY4=0,"",AEZ4/AEY4) =IF(AEY13=0,"",AEZ13/AEY13) =IF(AEU34=0,"",AEZ34/AEU34) =IF(AEU39=0,"",AEZ39/AEU39) =IF(AEU42=0,"",AEZ42/AEU42) =IF(AEU45=0,"",AEZ45/AEU45) =IF(AEU47=0,"",AEZ47/AEU47)
AFB	3	Passing Rate for Campus =(AEZ4+AEZ13+AEZ21)/(AEY4+AEY13+AEY21) =IF(AFA34<67%,"NO","YES") =IF(AFA39<67%,"NO","YES")
AFC	Empty	Empty

Appendix 3

DDDM

Data Driven Decision Making

RESOURCES	ACTIVITIES	OUTPUTS	IMMEDIATE OUTCOMES	LONG TERM OUTCOME
CPAD	Identifying Students: GT, At-risk, SPED, LEP	Academic Success	Reduce at-risk status of low SES background and/or challenged ethnic background	Enter post-secondary education
Eduphoria	Tutoring	TELPAS appropriate exit of bilingual program		Graduate from high school
AYP	Effectiveness of Interventions	Teacher awareness of student progress:	Increase likelihood of high school graduation	Students equipped with resources, experiences, academic achievement and background to graduate high school & prepared for college and career success
AEIS	Test readiness= Commended	Appropriate individual student goal setting	Increase college/career preparedness	
TELPAS	unprepared vs. prepared	Progress on Accountability	Increase college/career preparedness	
TAKS	Teacher effectiveness	Effectiveness of English/Spanish	Remedy academic insufficiencies	
Item Analysis	Staff development	Effectiveness of adequate coverage of tested curriculum	Properly address academic	Students contributing to society with high expectations
PEIMS	Lesson content - re-teach or re-visit		Accountability measures met and exceeded	
TPRI/DRA (grades 3-5)	Early promotion of commended			Increasing human capital
		Identifying individual mastery/non-mastery of TEK		

Appendix 4

CPAD

Comprehensive Powerful Academic Data

RESOURCES	ACTIVITIES	OUTPUTS (something produced)	IMMIDIATE OUTCOMES (something that follows as a result of consequence)		LONG TERM OUTCOME
Teachers	PLCs	Comprehensive Campus Data	Ability to Set Goals	Ability to Identify Strengths and Weaknesses	Increased Team Effectiveness
Administration	Tutoring		Ability to Track Progress Towards Goals		
Instructional Coaches	Mock Testing				Building Professional Capacity
Large Scale Color Printe	Campus Improvement Planning	Real Time Data	Ability to Adjust Individual Student Goals	Identification of Gifted and Talented Students	
Computer					Increased Likelihood of Graduating from High School
11x17 Paper	Initial Goal Setting Meetings		Ability to Adjust Campus Goals	Appropriate placement of LEP Students	
Microsoft Office		Flexible Data			Consistent Progress Towards Meeting State and Federal Ever Increasing Accountability Measures
TEKS	Follow Up/Progress Towards Goals Meetings		Increased Student Attendance	Appropriate exit of LEP Students	
TAKS Scores					
Mock Assessment Scores		Flexible Personalized Data Reports	Meaningful and Consistent Data Driven Decision Making	Early Identification of Students in Need of Intervention	
Pertinent Data Reports	Meaningful Celebrations for Meeting Goals	Comprehensive Intervention Schedule	Data-driven PLC discussions	Ability to Cross Compare Data that is normally Segmented Due to Lack of Comprehensive Data Systems	2
Scanning/Scoring Software That Imports to Excel		Individual Student Data Customized to Class Period or Homeroom Placement	Ability to Identify Strengths and Weaknesses		

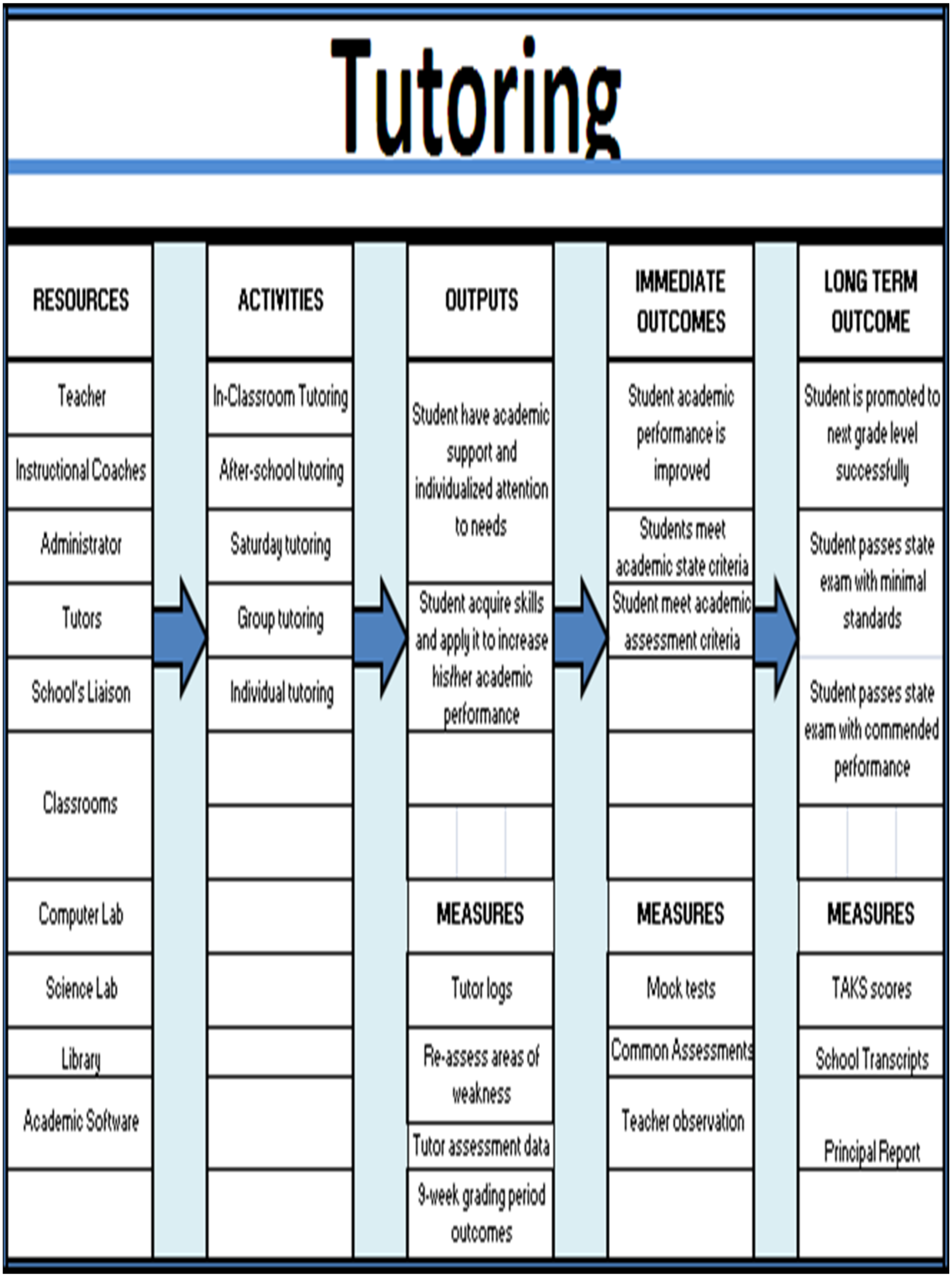
Appendix 5

PLCs

Professional Learning Communities

RESOURCES	ACTIVITIES	OUTPUTS	IMMEDIATE OUTCOMES	LONG TERM OUTCOME
Administrator	Item Analysis of every target student	Identify areas of weakness on subject area	Knowledge of student academic needs	Knowledge of student preparedness
Teachers	Collaboration by PLC to identify weaknesses of student expectations of the TEKS			Active monitoring of progress, performance, and curriculum of each student within each classroom of resources, materials, necessary for student academic achievement
Instructional Coaches		Teachers and administrators are actively monitoring student academic success and plan for necessary services based on student need	Plan tutoring sessions	
Mock Scores	Group students with similar intervention needs		Plan future assessments	
Benchmarks			Purchase needed resources and materials	
Common Assessments	Plan tutoring sessions			
	Identify needed resources and materials	Arrange for tutoring, testing, goal setting, staff development and training		
District Personnel				
	Plan to re-assess areas of weakness	**MEASURES**	**MEASURES**	**MEASURES**
	Adjust students in and out of interventions based on data	Targeted student's decrease after each mock assessment	Mock Tests	Teacher Report
			Common and District Assessments	Principal Report
		Weekly PLC meetings to identify students	Teacher observation	

Appendix 6


Tutoring
RESOURCES
ACTIVITIES
OUTPUTS
IMMEDIATE OUTCOMES
LONG TERM OUTCOME
Teacher
Instructional Coaches
Administrator
Tutors
School's Liaison
Classrooms
Computer Lab
Science Lab
Library
Academic Software
In-Classroom Tutoring
After-school tutoring
Saturday tutoring
Group tutoring
Individual tutoring
Student have academic support and individualized attention to needs
Student acquire skills and apply it to increase his/her academic performance
Student academic performance is improved
Students meet academic state criteria
Student meet academic assessment criteria
Student is promoted to next grade level successfully
Student passes state exam with minimal standards
Student passes state exam with commended performance
MEASURES
Tutor logs
Re-assess areas of weakness
Tutor assessment data
9-week grading period outcomes
MEASURES
Mock tests
Common Assessments
Teacher observation
MEASURES
TAKS scores
School Transcripts
Principal Report

Appendix 7

Mock Testing

An Assessment used from released State Tests

RESOURCES	ACTIVITIES	OUTPUTS	IMMEDIATE OUTCOMES	LONG TERM OUTCOME
Teacher	Administer test inside each classroom	udent level of performan	Improved student academic success	Student academic success
Instructional Coaches	Separate students based on need and same criteria to meet state guidelines for students with special needs	Identify weak TEKS	Improved teacher delivery of lesson	Teacher success
Administrator		Re-Plan tutoring sessions	Immediate knowledge of student progress/performance	
Pencils		Re-Plan Goal Setting		
Paper	Administer test in same format as "real" state	Re-Plan staff development		
Erasers	Mock tests are administered in the following months: October, December,	Re-Plan Training		
Scanner/Printer				
Bubble sheet Answer Documents	Each Mock test passing percentages are as follows: October = 45% December = 60%,			
		MEASURES	MEASURES	MEASURES
		Mock Assessment	Student Grades	Principal Report
				District Assessment Reports

Appendix 8

Goal Setting Meetings

RESOURCES	ACTIVITIES	OUTPUTS	IMMEDIATE OUTCOMES	LONG TERM OUTCOME
Administrator	Keeping the END result in the forefront	Establish	Motivation	Significant
Instructional Coaches	Clearly state objective	Strategize		Measureable
Teachers	Accountability	Plan	Self-Confidence	Action-Oriented
	Achieve highest potential	Execute	Significant	Rewarding
	Set differentiated goals for individual students	Review	Meaningful	Trackable
			Attainable	
			Relevant	
		MEASURES	MEASURES	MEASURES
		PLC Meetings	Principal Report	Principal Report
			Mock Tests	
		Mock Tests Results	TAKS Scores	

Appendix 9

Staff Development/Training

RESOURCES	ACTIVITIES	OUTPUTS	IMMEDIATE OUTCOMES	LONG TERM OUTCOME
Administrators	Meaningful ways to approach new ideas	Expand or change	Teachers use new methods from what they have learned in their classrooms	Broaden Teacher perspectives
Instructional Coaches	New technology	New Technologies		More knowledgeable
Teachers	New methods	Address any shortcomings	Knowledge/Beliefs	Adopting new practices
Presenters	Scientific based research	Enhance Communication	Positive Attitude	
Trainers	Improve self efficacy	Friendly competition	Increase in effective skills	Reduction of Student failures
	Lesson delivery	Minimize professional errors	Motivation	
	Using CPAD	Improve professional capacity	Positive behavior	
	Item Analysis	Motivate and improve teacher retention		
	TEKS standards	MEASURES	MEASURES	MEASURES
		Staff Development Reports	TAKS scores	Principal Report
			Mock Assessment Results	
		Teacher Participation	Common Assessment Results	

IRB Approval Forms

THE UNIVERSITY OF TEXAS AT EL PASO
Office of the Vice President for Research and Sponsored Projects
Institutional Review Board
El Paso, Texas 79968-0587
phone: 915 747-8841 fax: 915 747-5931

FWA **No: 00001224**

DATE: July 2, 2013

TO: Sarah Chavez-Gibson, B.S., M.Ed.

FROM: University of Texas at El Paso IRB

STUDY TITLE: [296404-1] THE COMPREHENSIVE, POWERFUL, ACADEMIC DATABASE (CPAD): AN EVALUATIVE STUDY OF A PREDICTIVE TOOL DESIGNED FOR ELEMENTARY SCHOOL PERSONNEL IN IDENTIFYING AT- RISK STUDENTS THROUGH PROGRESS, CURRICULUM, AND PERFORMANCE MONITORING

IRB REFERENCE #: 296404-1

SUBMISSION TYPE: New Project

ACTION: DETERMINATION OF EXEMPT STATUS

DECISION DATE: July 1, 2013

Thank you for your submission of New Project materials for this research study. University of Texas at El Paso IRB has determined this project is EXEMPT FROM IRB REVIEW according to federal regulation 45 CFR 46.101(b)(4).

Exempt protocols do not need to be renewed. Please note that it is the Principal Investigator's responsibility to resubmit the proposal for review if there are any modifications made to the originally submitted proposal. This review is required in order to determine if "Exemption" status remains.

We will put a copy of this correspondence on file in our office.

If you have any questions, please contact Athena Fester at (915) 747-8841 or afester@utep.edu. Please include your study title and reference number in all correspondence with this office.

CC:

El Paso Independent School District

Research and Evaluation

August 7, 2012

Sarah Chavez-Gibson 141 Tomillo Flats Dr. Chaparral, NM 88081

Dear Ms. Chavez-Gibson,

We have received your request to conduct research in the El Paso Independent School District. Congratulations your study, *CPAD: Comprehensive, Powerful, Academic Data to Identify At-Risk Students Through Progress, Curriculum, and Performance Monitoring by Using a Predictive Tool Designed for Elementary School Personnel,* has been approved. You will conduct the research using data from Bliss, Lend and Travis Elementary schools under the endorsement of Maria Flores, Associate Superintendent Elementary Division. As part of this approval, we require that you send a summary of your findings to our department for our records once your study is completed.

You have our best wishes for a successful study. Please contact me at (915) 230-2709 or email me at cperales@episd.org if you have questions. Thank you.

Sincerely

Carlos Perales
Researcher

cc: Maria Flores, Associate Superintendent Elementary Division

Approved:

James Steinhauser, Assistant Superintendent

Education Center-Boeing
6531 Boeing Drive • El Paso, Texas 79925 • (915)881-2400 • FAX (915) 771-1145
Mailing Address: P.O. Box 20100 • El PCISO, Texas 79998-0109

Curriculum Vitae

Sarah Chavez-Gibson was born in 1972 and raised in El Paso, Texas. She was born to Sarah Acosta and Allan Joe Chavez. However, after her father's death, her father's parents, Herbert and Mary Chavez, adopted her in 1979. Sarah has a sister from Sarah Acosta, named Jessica. Sarah has two uncles named Bruce and Jerome from Herbert and Mary Chavez that she considers brothers.

Sarah attended Holy Trinity Catholic School, Charles Middle School, Andress High School in El Paso, Texas, and graduated from William B. Travis High School in Austin, Texas. During and after graduating from high school, Sarah worked for major corporations such as Procter and Gamble, and IBM. Sarah also started a trucking company with her ex-husband, Billy Gibson, where they traveled the Continental United States and honored major contracts with the Department of Defense relocating highly sensitive materials. Among the attendance at Austin Community College, and The University of Texas, Sarah graduated from Park University where she majored in Computer Information Systems, later obtained her Masters in Education degree, and joined the Doctoral Program at The University of Texas at El Paso in 2007. In May of 2013 she defended her dissertation.

Sarah began her educational career as a substitute teacher, instructional para-professional, and technology teacher for all grade levels, K-12, taught robotics, computer animation, graphic design, Advance Placement courses, and other college and career readiness skills essential for the 21st century. In 2009, she left the classroom to become an elementary school assistant principal.

Sarah currently lives on a ranch in Chaparral, New Mexico, with daughter, and several farm animals. Sarah's daughter, Sarah Marie was 10 years old during the time of the writing of

this dissertation, and she had been promoted from 5^{th} to 6^{th} grade. All of Sarah's family has been wonderfully supportive.

Permanent address: 10417 Gaius Dr., El Paso, Texas 79924

This dissertation was typed by Sarah Chavez-Gibson