FINDING THE NEXUS BETWEEN A PREDICTIVE MATHEMATICS ASSESSMENT AND A NATIONAL STANDARDIZED MATHEMATICS ASSESSMENT IN AN ELEMENTARY SCHOOL

by

Jacqueline R. Royer

A Dissertation

Submitted to the
School of Graduate and Professional Studies
In partial fulfilment of the requirement
For the degree of
Doctor of Education
at
Delaware Valley University
January 9, 2020

DELAWARE VALLEY UNIVERSITY

Documentation of Final Defense of Dissertation

Title of Dissertation: **Finding the Nexus between a Predictive Mathematics Assessment and a National Standardized Mathematics Assessment in an Elementary School**

Author: Jacqueline R. Royer

Donna W. Jorgensen, Ed.D. — Donna W. Jorgensen
Chairperson

Todd A. Fay, Ed.D. — Todd A. Fay
Committee Member

Alyssa M. Walloff, Ed.D. — Alyssa Walloff
Committee Member

On behalf of Delaware Valley University:

John R. Woznicki

John R. Woznicki, Ph.D., Dean of the School of Graduate and Professional Studies

Todd A. Fay

Todd A. Fay, Ed.D., Director of Graduate Programs in Education

Date: January 9, 2020

Dedications

I would like to dedicate this manuscript to my loving family. To my late husband, Philip, who always believed in my dreams and encouraged me to make them come true. To my children Dan, Matthew, and Katherine. Dan for your support and for checking in periodically to see how everything was going. Matthew and Katherine for your unconditional love, support, and encouragement during this journey, especially when classwork took me away from being with you, and for always being there when I needed a friendly voice of reason. To my siblings, Barbara, Steven, Kim, and Susan, who continually encouraged and supported me throughout my entire life. Finally, to my late father, Michael, and my mother, JoAnne, for fostering a love of learning from an early age and helping me realize that no goal is out of reach. I am thankful for every one of you; you have helped to mold who I am today because of your love, support, and encouragement.

Acknowledgements

I would like to express my appreciation to my committee members for their guidance and support through the dissertation process. Dr. Jorgensen (Dr. J.), I am very fortunate to have had you as my committee chair. You were a great resource at any time during the day or night. You were quick to respond and provided invaluable guidance and support throughout the dissertation process. I value our friendship that was fostered along the way. Dr. Fay, thank you for all of the encouragement and help you have provided me over the last several years. I am thankful for your friendship, the inspiration that you provided me, and for always believing in me even when I didn't believe in myself. Dr. Walloff, I appreciate all of the knowledge that you instilled in me during the writing process. Your questioning techniques helped to stretch my thinking and to look at topics from a different viewpoint. I appreciate all of the support that you have provided me throughout the dissertation process.

Second, I would also like to express my appreciation to the Delaware Valley University Doctoral Cohort 3 members. We have been through many experiences together over the years and were always there to help and support one another. I will cherish all of the friendships that developed along the way.

Finally, I would like to acknowledge my extended family, friends and colleagues who have supported and encouraged me on this journey. The frequent check-ins and words of advice were greatly appreciated.

Abstract

Jacqueline R. Royer
FINDING THE NEXUS BETWEEN A PREDICTIVE MATHEMATICS ASSESSMENT AND A NATIONAL STANDARDIZED MATHEMATICS ASSESSMENT IN AN ELEMENTARY SCHOOL
2019-2020

The purpose of this quasi-experimental quantitative research study was to determine if there is a nexus between the accuracy of the score band predictive ability of the LinkIt!© mathematics assessment and the Partnership for Assessment of Readiness for College and Career (PARCC) mathematics assessment score band results. This research study looked at LinkIt!© mathematics assessment and PARCC mathematics assessment data from a two year period, 2016-2017 and 2017-2018, in one elementary school in New Jersey.

Using LinkIt!© formative assessment and PARCC summative assessment data, the study examined four questions focusing on accuracy and prediction for the total school, for three subgroups, and grade levels (grades three through eight) with a sample size ranging from 211 to 219. Descriptive statistics, a one way ANOVA, and a Pearson r correlation research methods were used to analyze the data. The accuracy prediction rate percentages for the total population ranged from 55.3% to 68.3%. The subgroup analyses revealed that no significant difference was noted, except one time between the special education and gifted and talented students (p=0.034). A significant positive correlation was noted between the LinkIt!© predictive mathematics assessment score bands and the actual PARCC mathematics assessment score band for all of the LinkIt!© assessment. The grade level analysis indicated that out of the six LinkIt!© forms studied, grade five had the highest accuracy rate 50% of the time.

Table of Contents

Abstract v

List of Figures x

List of Tables xi

Chapter One: Introduction 1

Overview 1

Need for the Study 9

Statement of the Problem 10

Definitions of Terms 11

Limitations and Delimitations 13

Research Questions 14

Research Hypotheses 14

Summary 17

Chapter Two: Literature Review 19

Introduction 19

History of Assessment 20

Elementary and Secondary Education Act of 1965 (ESEA). 20

No Child Left Behind Act of 2001 (NCLB). 21

Every Student Succeeds Act of 2015 (ESSA). 22

Assessment Theory 22

Table of Contents (continued)

Learning Theory 24
Behaviorism. 25
Cognitivism. 26
Constructivism. 26
Connectivism. 28
Formative and Summative Assessments 29
Formative assessments. 30
Summative assessments. 30
Psychometrics 31
Predictive Analytics 32
Data Warehouse and Data Mining 33
Data Driven Decision Making (DDDM) 34
Summary 35
Research Questions 36
Chapter Three: Methodology 39
Introduction 39
Research Questions 41
Setting 43
Subjects 44

Table of Contents (continued)

Instruments 46

LinkIt!© 46

LinkIt!© 48

PARCC assessment.. 50

PARCC validity and reliability. 57

Design of the Study 61

Procedures 61

Data Sources.. 62

Data Analysis Summary.. 63

Chapter Four: Results 64

Introduction 64

Data Analysis 65

Research Question 1.. 67

Research Question 2.. 71

Research Question 3.. 76

Research Question 4.. 90

Summary 94

Chapter Five: Discussion 96

Summary of the Study.. 96

Table of Contents (continued)

Summary of the Results 97

Research question 1. 97

Research question 2. 98

Research question 3. 99

Research question 4. 99

Relationship to Prior Research 101

Recommendations for Further Research 102

Implications for Practice and the Profession 104

Conclusion 106

References 109

Appendix A: IRB Approval 124

Appendix B: Letter of Interest 125

Appendix C: District Consent to Conduct Research 128

Appendix D: Revised Research Questions to District 129

Appendix E: Research Question 4 Tables 131

List of Figures

Figure Page

Figure 1. Prediction rates for 2016-2017 and 2017-2018 71

List of Tables

Table Page

Table 1. Students Enrolled in Each Grade Level 44

Table 2. Sub Group Population Count 45

Table 3. Amount of Time Allocated for the PARCC Assessment for the 2016-1017 and 2017-2018 school years 51

Table 4. PARCC Grade Level Cutoff Ranges for 2016- 2017 and 2017-2018 Testing Years 57

Table 5. LinkIt!© Prediction Assessment Accuracy Rates for Predicting Actual PARCC Assessment Scores 2016-2017 68

Table 6. LinkIt!© Prediction Assessment Accuracy Rates for Predicting Actual PARCC Assessment Scores 2017-2018 70

Table 7. ANOVA Results for the LinkIt!© 2016-2017 Form A Subgroup Comparison 73

Table 8. ANOVA Results for the LinkIt!© 2016-2017 Form B Subgroup Comparison 74

Table 9. ANOVA Results for the LinkIt!© 2016-2017 Form C Subgroup Comparison 74

Table 10. ANOVA Results for the LinkIt!© 2017-2018 Form A Subgroup Comparison 75

Table 11. ANOVA Results for the LinkIt!© 2017-2018 Form B Subgroup Comparison 76

Table 12. ANOVA Results for the LinkIt!© 2017-2018 Form C Subgroup Comparison 76

Table 13. 2016-2017 LinkIt!© Form A Mathematics Score Band and 2016-2017 PARCC Mathematics Score Band Skewness and Kurtosis Analysis..............78

Table 14. 2016-2017 LinkIt!© Form A Mathematics Score Band and 2016-2017 PARCC Mathematics Score Band Correlation 79

Table 15. 2016-2017 LinkIt!© Form B Mathematics Score Band and 2016-2017 PARCC Mathematics Score Band Skewness and Kurtosis Analysis..............80

List of Tables (continued)

Table 16. 2016-2017 LinkIt!© Form B Mathematics Score Band and 2016-2017 PARCC Mathematics Score Band Correlation 81

Table 17. 2016-2017 LinkIt!© Form C Mathematics Score Band and 2016-2017 PARCC Mathematics Score Band Skewness and Kurtosis Analysis..............82

Table 18. 2016-2017 LinkIt!© Form C Mathematics Score Band and 2016-2017 PARCC Mathematics Score Band Correlation 83

Table 19. 2017-2018 LinkIt!© Form A Mathematics Score Band and 2017-2018 PARCC Mathematics Score Band Skewness and Kurtosis Analysis..............84

Table 20. 2017-2018 LinkIt!© Form A Mathematics Score Band and 2017-2018 PARCC Mathematics Score Band Correlation 85

Table 21. 2017-2018 LinkIt!© Form B Mathematics Score Band and 2017-2018 PARCC Mathematics Score Band Skewness and Kurtosis Analysis..............86

Table 22. 2017-2018 LinkIt!© Form B Mathematics Score Band and 2017-2018 PARCC Mathematics Score Band Correlation 87

Table 23. 2017-2018 LinkIt!© Form C Mathematics Score Band and 2017-2018 PARCC Mathematics Score Band Skewness and Kurtosis Analysis..............88

Table 24. 2017-2018 LinkIt!© Form C Mathematics Score Band and 2017-2018 PARCC Mathematics Score Band Correlation 89

Table 25. 2016-2017 and 2017- 2018 Grade Level LinkIt!© Mathematics Lower Prediction Percentages 92

Table 26. 2016-2017 and 2017- 2018 Grade Level LinkIt!© Mathematics Accuracy Prediction Percentages 92

Table 27. 2016-2017 and 2017- 2018 Grade Level LinkIt!© Mathematics Higher Prediction Percentages 93

Table 28. 2016-2017 LinkIt!© Mathematics Form A...131

Table 29. 2016-2017 LinkIt!© Mathematics Form B...131

Table 30. 2016-2017 LinkIt!© Mathematics Form C...132

Table 31. 2017-2018 LinkIt!© Mathematics Form A...132

List of Tables (continued)

Table 32. 2017-2018 LinkIt!© Mathematics Form B...133

Table 33. 2017-2018 LinkIt!© Mathematics Form C...133

Chapter One: Introduction

Overview

The impact of mandated standardized testing has been at the forefront of educational conversations and policies since the late decades of the 20th century and into the first decades of the 21st century. Scores on these assessments can be used to determine if a student meets the predetermined criteria for advanced placement classes, assign a student to remedial courses, and can even determine if a student will be able to graduate high school. As assessment mandates have increased, the stakes for the students and schools have escalated.

With the passage of the 2001 No Child Left Behind Act (NCLB), a reauthorization of the Elementary and Secondary Education Act of 1965 (ESEA), the federal government's role in state and school district accountability increased with the requirement of states and school districts needing to show progress in student performance (Robelen, 2005). The NCLB Act required states to test students each year in grades three through eight as well as once between ninth and twelfth grade, in the mathematics and reading content areas (Klein, 2015). School districts in each state were also required to assess students in the science content area once in grades third through fifth, sixth through eighth, and tenth through twelfth (Skinner and Kuenzi, 2015). In 2015, the Elementary and Secondary Education Act of 1965 (ESEA) was reauthorized again and renamed the Every Student Succeeds Act (ESSA) (Congressional Digest, 2017). Some of the benefits of the 2015 ESSA reauthorization include giving states more control over: assessments, schools that are low performing, and the quality of teachers in the schools (Klein, 2016).

Prior to the passage of the 2001 No Child Left Behind Act (NCLB) and its reauthorization, the 2015 Every Student Succeeds Act (ESSA), New Jersey required students in the state to participate in mandated assessments. According to the State of New Jersey Department of Education (NJDOE) website, New Jersey started administering the first mandated standards-based assessment in 1979 in the areas of reading and mathematics. The NJDOE website shows that assessments were developed in the following years:

- 1979 - Minimum Basic Skills (MBS) Assessment - administered in grades three, six and nine
- 1983 - High School Proficiency Test (HSPT9) - administered in Grade 9
- 1988 - High School Proficiency Test (HSPT11) - the state moved the HSPT9 to grade 11 and also added a grade eight assessment called the Grade 8 Early Warning Assessment (EWT)
- 1997 - The Elementary School Proficiency Assessment (ESPA) - administered to fourth grade students
- 1998 - The Grade Eight Proficient Assessment (GEPA) - this assessment took the place of the Early Warning Test (EWT)
- 2001 - The High School Proficiency Assessment (HSPA) - this assessment took the place of the HSPT11
- 2004 - The New Jersey Assessment of Skills and Knowledge (NJ ASK) was operational for grades three and four
- 2006 - The New Jersey Assessment of Skills and Knowledge (NJ ASK) - grades five, six and seven were added

- 2015 - Partnership for Assessment of Readiness for College and Career (PARCC) - replaced the NJ ASK, GEPA and the HSPT11. (https://www.nj.gov/education/assessment/history.shtml)

Although assessments have been implemented in New Jersey since 1979, the implementation of the Partnership for Assessment of Readiness for College and Career (PARCC) assessment created an outcry from many stakeholders in the state. In 2015, when the State of New Jersey began the implementation process for the PARCC assessment, the numerous stakeholders reacted in very different ways. Behind the scenes, the various stakeholder groups were conducting many activities.

Although New Jersey had been requiring students to take assessments for many years, the way the Partnership for Assessment of Readiness for College and Career (PARCC) assessment was introduced did not sit well with some parents. As a result, parents were starting to gather and make phone calls to other parents in hopes of providing a united front in opposition to the new mandated assessments. Parents were attending Board of Education meetings, talking with school district personnel, and opting their children out of taking the assessment.

Some of the newspaper headlines during the first year of implementation of the PARCC assessment captured the tone of the parent opposition. One example occurred on March 7, 2015, when the Washington Post published an article titled: “Some parents around the country are revolting against standardized testing.” The article highlighted the parents’ concerns about the amount of time teachers were taking away from instruction to get the students in their class ready for the PARCC assessment. It also stressed the concerns about the new accountability measures of using the results of the assessment to make judgement on principals, teachers, and schools. As indicated in the article, parents were also “opting” their children out of taking the PARCC assessment. (https://www.washingtonpost.com/local/education/some-parents-across-the-country-are-revolting-against-standardized-testing/2015/03/05/e2abd062-c1e1-11e4-9ec2-b418f57a4a99_story.html?utm_term=.fff2cf30b3d1)

Students also took part in resisting the implementation of the PARCC assessment. They attended New Jersey Board of Education meetings to discuss their displeasure in taking the mandated assessment. At these meetings, they also testified about how stressful it was to take the PARCC assessment. Newspaper headlines highlighted the students’ dissatisfaction with taking the assessment. The following headline, from a January 15, 2015 Washington Post article, was written after a student had testified in front of the New Jersey Board of Education: “Teen: The PARCC Common Core test is ‘the most stressful thing I’ve done in school’.” In this article, reporter Valerie Strauss reports on the testimony of a high school freshman who was speaking in front of the New Jersey Board of Education. In the testimony, the student indicated that it is very stressful to take the PARCC assessment. The student discussed how irrelevant the topic of the Research Simulated Task was and how difficult it was to write an equation using the computer. Finally, the student also discussed how teachers are not able to teach in the manner they would like to and the student relayed a story about one of his favorite teachers who is thinking of retiring because she is not able to teach the way she had in the past (https://www.washingtonpost.com/news/answer-sheet/wp/2015/01/15/teen-the-parcc-common-core-test-is-the-most-stressful-thing-ive-done-in-school/?utm_term=.cd7c9a3b8985).

As with the parents and students, teachers were also becoming upset about the rollout of the PARCC assessment. According to an nj.com, article titled, "NJEA launches ad campaign against PARCC tests" written on February 17, 2015, the New Jersey Education Association (NJEA), the largest teachers' union in New Jersey, set up a media campaign against the implementation of the PARCC assessment. As indicated in the article, over a six-week period, the NJEA showed advertisements online and on television to show their objections to the assessment. The article also stated that the union was against the state's decision to have the assessment tied to teacher evaluations starting in the 2015-2016 school year (see https://www.nj.com/education/2015/02/njea_launches_ad_campaign_against_parcc.html). As indicated above, as part of the accountability aspect of the PARCC assessment, the teachers were now going to have their evaluation scores tied to the results of the PARCC assessment. This caused some teachers to react in a negative manner. They were not happy about the new change and worried that working with struggling students would affect their evaluation scores in an adverse way. According to a New York Times article written on March 1, 2015, titled "As Common Core Testing Is Ushered In, Parents and Students Opt Out," teachers in New Jersey were concerned that ten percent of their summative evaluation score would be connected to the results of the PARCC assessment. (https://www.nytimes.com/2015/03/02/nyregion/as-common-core-testing-is-ushered-in-parents-and-students-opt-out.html)

According to the 2001 NCLB Act and the 2015 ESEA Act, 95% of the students in each school district, total population and sub group populations, must be assessed on the summative assessment (Skinner and Kuenzi, 2015). According to an April 22, 2015

nj.com article titled, *"*N.J. schools with high PARCC opt outs could have to make changes, education commissioner says.*"* The article indicated that school districts that did not meet the 95% participation rate will be required to complete a corrective action plan and schools with excessively high non participation rates could lose some of their state funding.
(https://www.nj.com/education/2015/04/nj_education_commissioner_pledges_sanctions_over_p.html)

The New Jersey School Boards association published a FAQ page on their website to address the questions that may arise in a school district about the PARCC implementation. The following response was written to answer the question, "What will be the impact on the state if students do not participate in PARCC?"

> In a December 21, 2015 letter to all chief state school officers, the U.S. Department of Education advised the following: "If a State with a participation rate below 95 percent in the 2014-2015 school year fails to assess at least 95 percent of its students on the statewide assessment in 2015-2016, the U.S. Department of Education has a range of enforcement actions at its disposal. These include the following:
>
> 1. Withholding Title I, Part A State administrative funds;
>
> 2. Placing the State's Title I, Part A grant on high-risk status and directing the State to use a portion of its Title I State administrative funds to address low participation rates; or
>
> 3. Withholding or redirecting Title VI State assessment funds.

> The USDOE will consider the appropriate action to take for any State that does not assess at least 95 percent of its students in 2015-2016, both overall and for each student subgroup among its LEAs. To determine what action is most appropriate, the USDOE will consider state and local participation rates for 2015-2016, as well as action the state has taken with respect to any local school district noncompliance with the assessment requirements under ESSA. (https://www.njsba.org/wp-content/uploads/2016/02/parcc-faq16.pdf)

As the stakeholders were expressing their concerns, the implementation of the 2015 PARCC assessment began. During the first year of the full implementation, many parents in New Jersey decided to "opt" their children out of taking the assessment. Based on information gathered from the NJDOE website Title I Accounting section, during the 2015 PARCC administration, 23% of the school districts, including charter schools, did not meet the 95% threshold for participation in the mathematics section of the assessment (www.nj.gov/education/title1/accountability/progress/15/districts.shtml).
The results were similar during the 2016 administration of the PARCC assessment with 25% of the school districts, including charter schools, not meeting the participation requirement (www.nj.gov/education/title1/accountability/progress/16/districts.shtml). As a result of the parents "opting" their children out of the assessment, several school districts did not reach the 95% assessment rate and needed to complete a corrective action plan on how they would make sure this would not happen in the future (https://www.nj.gov/education/title1/accountability/progress/15/ActionPlan.pdf).
Given that there is a lot at stake for students, teachers, and schools when taking the PARCC assessment, it was important to find a teaching tool to guide instruction.

Teachers want the benefit of knowing exactly what skills their students are lacking so they can teach these skills to their students prior to the PARCC assessment administration. Therefore, when faced with the dilemma of how to help the students in a district, school district leaders and teachers continually search for ways to help students succeed on the state mandated summative assessment. When looking at the various alternatives, utilizing commercially produced formative assessments is one way that school districts can help the students in their school district be successful on the mandated summative assessments. Formative assessment, as defined by Guskey & McTighe (2016), is the approach that educators use to decide what the students in their class have learned. Summative assessment, according to Agboola, & Hiatt (2017), "is an assessment of learning that is usually used for high-stakes purposes" (p. 76). PARCC is a summative assessment.

Formative assessments help provide the teacher with valuable information on the strengths or weaknesses in a student's learning. They can be teacher made or purchased through an educational vendor. Students can use a computer or a paper and pencil version to complete the assessments. Formative assessments could also be just a few minutes of observation. Although it does not matter in what form a formative assessment is given, the important aspect is that it provides valuable information to the teacher on the areas of strengths and weaknesses for each student. Therefore, it is important for teachers to administer formative assessments to gain valuable knowledge on what the students still need to learn before they complete the summative assessment.

Need for the Study

Since school districts are required under the provisions of the 2001 NCLB Act and the 2015 ESSA Act to assess students in grades three through eight and one time in high school, it is important to determine if the formative assessment tools being used in school districts are providing the expected results. LinkIt!© is one possible commercially produced formative assessment option. LinkIt!© is a computerized assessment and databank program that assesses both Language Arts and Mathematics. One aspect of the LinkIt!© program is the three formative assessment forms that students complete at different times during the school year. The results from these assessments are then analyzed in the Navigator report provided by LinkIt!©. As part of the assessment process, LinkIt!© provides a predictive assessment score band that reflects how the student might score on the PARCC mathematics assessment. There is a gap in the research in determining if the predictive capabilities of the LinkIt!© mathematics assessment tool is accurate in the predictions of how a student might score on the PARCC mathematics assessment. Therefore, this research study looked at the accuracy of the LinkIt!© predictability capability for the total number of student score band results as well as score bands broken out by grade levels for the students who took both the LinkIt!© and PARCC mathematics assessments. The research study also analyzed three subgroups of students (general education, special education, and gifted and talented) to determine if there was a difference in accuracy rates. Last, the study also determined if there was a relationship between the LinkIt!© mathematic assessment predicted PARCC score band and the actual PARCC mathematic assessment score band.

Statement of the Problem

With the assessment mandates implemented in the 2001 No Child Left Behind Act (NCLB) and continued in the current 2015 Every Student Succeeds Act (ESSA), school districts are continually looking for ways to help the students improve their scores on the state mandated assessment. Districts have many options at their disposal to help their students improve. Districts may choose to create their own internal assessments or purchase an assessment tool from an outside vendor to help predict how the students may score on the state mandated testing. Resources in school districts can be limited. Therefore, when a district chooses to purchase an assessment tool it is important to make sure the tool is able to produce the marketed results.

This research study reviewed one particular outside vendor's assessment tool, LinkIt!©, over a two-year period (2016-2017; 2017-2018), to see the frequency of accuracy between the student assessment results on the three LinkIt!© mathematics assessment forms and the LinkIt!© predicted PARCC mathematics assessment result, for both school years. The study also looked at accuracy rates for three subgroups: general education, special education, and gifted and talented. Using the same two-year period, this study looked at the relationship between the predicted outcome of the LinkIt!© mathematics assessment and the actual outcome on the New Jersey state mandated assessment, The Partnership for Assessment of Readiness for College and Careers (PARCC) mathematics results. Finally, the study analyzed data by grade level to determine if there was a difference in accuracy between grade levels.

Definitions of Terms

504 – "enacted in 1973, [it] was the first civil rights legislation that specifically guaranteed the rights of the disabled by prohibiting discrimination in programs or activities that receive federal funds" (Russo & Osborne, 2009, p. 22).

Accuracy Rate – For this research study, accuracy rate refers to score predictions that were lower than the actual score, accurate to the actual score and higher than the actual score.

Data Driven Decision Making – "the ongoing cycle of making choices and taking action based on multiple sources of data and frequent, thoughtful conversations with the larger school community" (O'Neal, 2012, p. 2).

Data Warehouse – "a repository of information collected from multiple sources, stored under a unified schema, and usually residing at a single site" (Han, Kamber & Pei, 2012, p. 10).

Every Student Succeeds Act of 2015 (ESSA) – "reauthorizes the 50-year-old Elementary and Secondary Education Act (ESEA), the nation's national education law and longstanding commitment to equal opportunity for all students." (https://www.ed.gov/essa?src=rn)

Formative Assessments – "Assessment during the course of instruction rather than after it is completed" (Santrock, 2011, p. G-4).

Gifted and Talented – "*New Jersey Administrative Code* 6A:8-3.1 defines students who are gifted and talented as those students who possess or demonstrate high levels of ability in one or more content areas when compared to their chronological peers in the local district and who require modification of their educational program if they are to achieve in accordance with their capabilities."

(https://www.state.nj.us/education/genfo/faq/faq_gandt.htm)

Individualized Education Plan (IEP) – **"**New Jersey Administrative Code for special education (N.J.A.C. 6A:14) and the federal Individuals with Disabilities Education Act of 2004 (IDEA 2004) are laws that ensure children with disabilities a free, appropriate public education in the least restrictive environment."

(https://www.nj.gov/education/specialed/form/prise/prise.pdf)

LinkIt!© – LinkIt!© is a "data warehouse, assessment solutions and analytics for administrators, students, parents and teachers." (http://www1.linkit.com/)

Predictive Assessments – Assessments that can make predications on future performance on other assessments.

Psychometrics – "Psychometrics is the science concerned with evaluating the attributes of psychological tests" (Furr, 2017, p. 9).

Score – Score will refer to a specific score band on the LinkIt!© mathematics assessments and PARCC mathematics assessments. These score bands will include the following categories for LinkIt!©: Did Not Met Expectations, Partially Met Expectations, Approaching Expectations, Bubble, Met Expectations, and Exceeded Expectations. The score bands categories for PARCC are as follows: Did Not Met Expectations, Partially Met Expectations, Approaching Expectations, Met Expectations, and Exceeded Expectations.

Summative Assessments – "Assessment after instruction is finished to document student performance: also called formal assessment" (Santrock, 2011, p. G-8). Students take summative assessments at the end of a particular instructional timeframe, after all of the material for that unit has been taught. At times, this type of assessment has been called high stakes assessments since they are assessing what knowledge the student has retained after all of the instruction has been completed.

The Partnership for Assessment of Readiness for College and Careers (PARCC) – "a collaboration of states that share a commitment to developing new-era assessments that measure students' readiness for college and career……. This includes readiness to master rigorous academic content at each grade level, think critically and apply knowledge to solve problems, and conduct research to develop and communicate a point of view." (https://parcc-assessment.org/about/)

Limitations and Delimitations

Limitations and delimitations are inevitable in most research studies. There are several limitations noted in this research study. One possible limitation of which to be aware is the use of only one predictive assessment tool over a two year period. This research study looked at only the predictive ability of the three LinkIt!© mathematics assessment forms as a predictor of the students' PARCC mathematics assessment score. Although the Every Student Succeeds Act (2015) requires states to assess students annually in grades three through eight and one time between ninth and twelfth grade (Skinner and Kuenzi, 2015), the ESSA does not mandate what assessment needs to be given in each state. There are many different summative assessments throughout the United States, and PARCC is one of the offered assessment options. This research study looked only at the PARCC assessment.

Although there are two content areas, English Language Arts and Mathematics, assessed by LinkIt!© and the PARCC assessment, this research study looked at only the

Mathematics section of the assessment. The study also looked at only one small rural elementary school in central New Jersey. Therefore, this research study looked at a small school population.

Research Questions

1. What is the accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period?
2. When comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score, what differences in accuracy rates are revealed over the two-year period for each of the three forms, based on groupings of students in:
    - general education,
    - special education, and
    - gifted and talented education?
3. What is the relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score?
4. What is the accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period by grade level?

Research Hypotheses

This research study determined if the accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one elementary school over a two-year period is different. The following hypotheses were used to determine if there is a predictability between the two.

Null Hypothesis: There will be no difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period.

Alternative Hypothesis: There will be a difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period.

This research study looked at three sub-groups of subjects: general education students, special education students, and gifted and talented students. The following hypotheses were used to determine the accuracy rate for the LinkIt!© predictions of actual PARCC scores for three subgroups.

Null Hypothesis: When looking at sub-groups of students, there will be no statistically significant difference in accuracy rates over the two-year period for each of the three forms based on groupings of students in general education, special education, and gifted and talented education when comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score.

Alternative Hypothesis: When looking at sub-groups of students, there will be a statistically significant difference in accuracy rates over the two-year period for each of the three forms based on groupings of students in general education, special education, and gifted and talented education, when comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score.

In order to determine if there is a relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score the following hypotheses were used.

Null Hypothesis: There will be no statistically significant relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score.

Alternative Hypothesis: There will be a statistically significant relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score.

Finally, when determining the difference in accuracy rate of prediction by grade level between the LinkIt!© predictive mathematics assessment results across all three forms and the actual PARCC mathematics assessment score in one elementary school over a two-year period, the following hypotheses were used.

Null Hypothesis: There will be no difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period by grade level.

Alternative Hypothesis: There will be a difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period by grade level.

Summary

School districts throughout the United States continually look for ways to help their students succeed on mandated summative assessments originally required by the 2001 No Child Left Behind Act (NCLB) and currently required by the 2015 Every Student Succeeds Act (ESSA). School districts are directed to assess students in grades three through eight and one time in high school (Skinner & Kuenzi, 2015, Sharp, 2016). Using formative assessments throughout the school year is one way to help school districts gather data to analyze and to drive instruction in order to help students improve academically. Since all students come to school at different ability levels, it is important for districts to find ways that might help predict how a student may score on these mandated assessments. One possible solution is using the LinkIt!© assessment platform. The LinkIt!© platform assesses students three times during the school year and makes a prediction based on the results on how a student may score on the mandated state assessment. “LinkIt! empowers educators at the classroom, school, and district level to make decisions that inform, monitor, and measure teaching and learning goals” (C. Marcus, personal communication, October 22, 2019).

This research study investigated the accuracy rate of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment results over a two-year period (2016-2017; 2017-2018). The study also focused on sub-group information (general education, special education, and gifted and talented), to determine if there are differences in accuracy between the two assessments. It also determined if there was a correlation between the LinkIt!© mathematics assessment PARCC predictive score band results and the actual PARCC mathematics assessment score band results, as well as the predictive accuracy by grade level over the two-year period. The literature review in Chapter Two focuses on the history of the 1965 Elementary and Secondary Act, assessment theories, learning theories, different types of assessments, along with various aspects of the gathering and using data to drive instruction. Chapter Three discusses the design of the study, instruments used, procedures, and data sources. Chapter Four reports on the findings of the data analysis, and Chapter Five provides a summary of the research study.

Chapter Two: Literature Review

Introduction

Starting with the passing of the Elementary and Secondary School Act (ESEA) in 1965 and up to the current reauthorization in 2015 called the Every Student Succeeds Act (ESSA), school districts are continually looking for ways to help the students in the school district meet required mandates. Mandated summative assessments are part of the requirements of the prior NCLB as well as the current ESSA. School districts have many options at their disposal to help their students improve on the state mandated assessments. One option might be to use formative assessments. When a school district is looking at their options, two questions might come to mind: 1. Do we create our own formative assessment tool to see how our students are doing or do we purchase an assessment tool from an outside vendor? 2. Will this assessment tool help predict how a student might score on the state mandated assessments? Taking a look at past research information is a helpful way to answer these questions.

This research study literature review concentrated on three major themes. In order to better understand why there are mandated assessments being administered, the first part will focus on the history of the Every Student Succeeds Act of 2015 and also touch on the topics of the Elementary and Secondary Act of 1965 and the No Child Left Behind Act of 2001. The second part will review the theoretical understandings behind the study and will include the topics of assessment theory, learning theory, formative and summative assessments, psychometrics, and predictive analytics. The third section will concentrate on how to store and analyze data including data warehouse, data mining, and data driven decision making.

History of Assessment

Elementary and Secondary Education Act of 1965 (ESEA). In 1965, President Lyndon Johnson's administration passed the Elementary and Secondary Education Act of 1965 (ESEA) (Nelson, 2016). The goal of the ESEA was to help students from lower socioeconomic families by allocating federal funds, through a Title I grant, that would help to balance the spending between wealthy and poor school districts (Casalaspi, 2017). Overall, the ESEA allocated funding for five different Title areas that helped to provide more funding for "schools, cultural centers, libraries, state's departments of education and cooperative research, all focused on addressing "disadvantaged" students" (Young, 2018, p. 79). Since 1965, the Elementary and Secondary Act of 1965 (ESEA) has been reauthorized several times. Below is a summary of some of the major reauthorizations of the ESEA that Sharp (2016) listed:

- 1978 – President Jimmy Carter reauthorized the ESEA on November 1, 1978
- 1981 – President Ronald Reagan reauthorized ESEA and also signed the Education Consolidation and Improvement Act (ECIA) on August 13, 1981
- 1994 – President Bill Clinton reauthorized the ESEA which included the Improving America's School Act (IASA) on October 20, 1994
- 2002 – President George W. Bush reauthorized the ESEA and renamed it the No Child Left Behind Act (NCLB) on January 8, 2002
- President Barack Obama reauthorized the ESEA and renamed it the Every Student Succeeds Act (ESSA) on December 10, 2015.

ESEA did not address assessment or standards on a national level but indicated that local and state authorities should look at the effectiveness of their assessments to make sure that there is equality in their educational system (Young, 2018). This research study includes the time from the reauthorizations of the No Child Left Behind Act of 2001 and the Every Student Succeeds Act of 2015; therefore, the following two sections will address the components of those two reauthorizations.

No Child Left Behind Act of 2001 (NCLB). In 2001, Congress passed the No Child Left Behind (NCLB) Act and President George W. Bush signed it into law on January 8, 2002 (Grey, 2010). This was one of the reauthorizations of the Elementary and Secondary Education Act of 1965 (ESEA) (Sharp, 2016). School districts were charged with getting 100% of their students on grade level by the year 2014 and, if the school districts did not make progress, there would be penalties (Jacob, 2017). Using standardized exams in the content areas of reading and math (Jacob, 2017), schools in every state needed to assess students who were in third through eighth grade and at least once between the tenth and twelfth grade years (Looney, 2011).

Accountability was a key component of NCLB since school districts were required to report "Adequate Yearly Progress" (AYP) and also analyze subgroups of students to see if there were inequalities in how the students performed (Piro, Dunlap, & Shutt, 2014, p. 2). Ninety-five percent of the students must participate in the state assessment, including all of the subgroup categories, as one of the conditions in making AYP (Skinner and Kuenzi, 2015). School districts, based on the number of years that they did not make AYP, may be required to send students to "another public school, with transportation paid by the LEA or using Title I funds to pay for a private tutor" (Shaul & Ganson, 2005, p. 156). Additionally, as part of the accountability to the public, NCLB required school districts to release the testing results to the public (Haretos, 2005). Although NCLB was due to be reauthorized in 2007 (Congressional Digest, 2017), the next reauthorization did not take place until 2015 (Sharp, 2016).

Every Student Succeeds Act of 2015 (ESSA). In 2015, the Every Student Succeeds Act of 2015 (ESSA) became law (Congressional Digest, 2017). With this reauthorization, the requirements for AYP were no longer included (Fennel, 2016). States were still required to annually assess the students in their school district with the ninety-five percent participation rate still in effect (Skinner and Kuenzi, 2015). According to the Congressional Digest (2017), ESSA continues to include safeguards to make sure that equity for disadvantaged students is still in place, adds a requirement that all students need to have college and career readiness skills from being instructed with high standards, and also continues the accountability requirement to make sure students in disadvantaged areas are still making educational progress and provide resources to help the school district improve if the district is not making progress. States are also still required to provide extra school improvement support to schools that fall into the bottom 5% of all the schools in the state (Klein, 2016). Mandated assessments have continued to be an essential component of the several reauthorizations of the Elementary and Secondary School Act of 1965. It is important to take a further look at the theory behind assessments.

Assessment Theory

As documented in history, psychology has been the foundation for assessment practices by considering mental characteristics and their evaluations (James, 2006). Assessment outcomes, as well as using a variety of other measurement data, are beneficial instruments for schools (Ghaicha, 2016). When considering assessment theories, it is useful to understand the following terms: assessment, measurement and evaluation. Gathering evidence around something so it can be used for a reason is a very simplistic definition of assessment written by Brookhart (2004). However, Ghaicha (2016) provides the following detailed definition:

> Assessment is operationally defined as a part of the education process where instructors appraise students achievements by collecting, measuring, analyzing, synthesizing and interpreting relevant information about a particular object of interest in their performance under controlled conditions in relation to curricula objectives set for their levels, and according to the procedures that are systematic and substantively grounded. (p. 213)

Measurement, a narrower term than assessment, can be defined as employing a set of requirements to a characteristic of a person or a thing to acquire quantitative data regarding it (Brookhart, 2004). Finally, evaluation can be described as using assessment results and making a conclusion about their value (Brookhart, 2004) and also as coming to a conclusion about intangible things (Ghaicha, 2016).

Although Ghaicha (2016) and Pattalitan (2016) express their definitions in different ways, they have similar thoughts in their definitions of assessment. Ghaicha (2016) provides the following three reasons for using assessments: generating judgments about learners, apprising teaching and acquiring knowledge, and improving programs and also for accountability. Pattalitan (2016) also indicates that there are three reasons for assessment: 1. Assessment *for* learning, 2. Assessment *as* learning, and 3. Assessment *of* learning.

Assessment is an influential force that can either enhance or undercut learners acquiring knowledge (Ghaicha, 2016). Although Brookhart (2004) indicates that the following four ways to gather assessment data: “paper and pencil assessment, performance assessments, based on oral communication, and portfolios” (p. 7), many assessments can also be completed using a computer. Once the assessment data is collected and analyzed, feedback must be given to the student. According to Brookhart (2004), feedback for assessment can be compiled in three different ways: “objectively scored numerical value, subjectively scored numerical value, and written feedback” (p. 7). Good assessment examines the improvement of the learner, decides the “performance levels” of the learners as well as the educators and also provides assessment on the course with the end goal of enhancing teaching and educator success (Ghaicha, 2016, p. 214). Although learning theorists do not typically make declarations about how assessment should be conducted within their learning theory (James, 2006), it is still important to look at the research behind learning theories in order to better understand the background behind assessments.

Learning Theory

Learning theories, according to Zhou (2007), look to answer two different questions: “what learning is and how learning takes place” (p. 131). James (2006) indicates that the most important learning outcomes permit students to be successful by allowing them to continue acquiring information, in any learning situation, especially since technology and information are constantly changing. One drawback of learning theories, as pointed out by Zhou (2007), is that they look at only a small part of learning: the attainment, organization, and construction of information. Yilmaz (2011), Zhou

(2007), and Nagowah, L. and Nagowah, S. (2009) agree that three main learning theories are behaviorism, cognitivism and constructivism. Although these authors are in agreement about the above three learning theories, this research study will also look at a newer learning theory called connectivism. It is important to take a closer look at each of the four learning theories to better understand their views on assessment.

Behaviorism. In the learning theory of behaviorism, James (2006) and Fischer (1973) agree that acquiring knowledge is based on external stimuli and the response that is given to that stimuli. Behaviorists use rewards and punishments, as needed, in response to the person's behavior (James, 2006). Behaviorism doesn't look at mental activities as being as important as observable behaviors (Nagowah, L. and Nagowah, S. 2009). Mergel, (1998) as cited in Nagawah, L. and Nagawah, S. (2009) and James (2006) agree that the most widely known psychologists associated with behaviorism are B. F. Skinner, Watson, Pavlov, and Thorndike. Out of the prior listed psychologists, the most commonly associated behaviorist is B. F. Skinner (Thomas, 2017). This theoretical viewpoint was influential during the 1960s and the 1970s and is still used in many educational practices as well as "behavior modification programs" (James, 2006, p. 7). Nagowah, L. and Nagowah, S. (2009) point out there are strengths and weaknesses to this theory. One strength is that the student is motivated by a well-defined objective and replies spontaneously when they see indications of the objective and one weakness it that the student may be in a situation, where a response is needed, but they will not have the background knowledge on how to react to that situation (Nagowah, L. & Nagowah, S. 2009). Assessment in the behaviorist learning theory, according to Duke, Harper, and Johnston (2013), is centered on whether certain conditions are met for each goal.

Cognitivism. Cognitivist theorists consider acquiring knowledge “as an active process of knowledge construction” (Yilmaz, 2011, p. 204). Gage and Berliner (1988) as cited by Nagowah, L. and Nagowah, S. (2009) state that theorists who use the cognitive approach use visual clues as they determine what is happening in the learner’s mind. James (2006) and Nagowah, L. and Nagowah, S. (2009) agree that the cognitivist theory highlights the importance of the mind in order for students to learn. Siemens (2004) compares the theory with the way that a computer processes information, with information being inputted, storing it in the short-term recall, and embedding it for future use. James (2006) points out that Chomsky, Simon, and Bruner are cognitive theorists; Yilmaz (2011) also adds Tolman, Piaget, Vygotsky, and Gestalt to the list. Using formative assessment is essential in this theory since it is important for teachers to understand how the learner is thinking and then differentiate instruction to accommodate their teaching to the needs of the students (James, 2006). According to Nagowah, L. and Nagowah, S. (2009), a strength of the cognitive theory is that the students are taught to complete the assignment the exact way numerous times. However, a weakness in this theory is that since the student learns to complete the assignment in a specific way, it might not be the appropriate way to complete the assignment in a particular circumstance.

Constructivism. Constructivists believe that learning is created in the student’s mind based on their prior encounters (Nagowah, L. & Nagowah, S. 2009; Simmens, 2004). Constructivism associates acquiring knowledge and the purpose of the brain to the internal mechanisms of a personal computers (Thomas, 2017). Instruction in the constructivist learning theory acknowledges that the student is actively involved in the learning process as they seek to make sense of the new information they are learning

(Mercer, Jordon, Miller, 1994) and their learning is not based on the teacher conveying the knowledge to them (Schcolnik, Kol, & Abarbanel, 2006). Piaget and Vygotsky are two theorists associated with the two types of constructivism. Piaget is associated with the cognitive constructivism theory and Vygotsky is associated with the social constructivism theory (Schcolnik et al., 2006).

Piaget's theory affirms that when a student is given new information they will unwittingly take the information and compare it to all of their prior learning and encounters (Colburn, 2007). The most important aspect in learning for a cognitive constructivism is the mind (Schcolnik et al., 2006). Using information learned from prior experiences, students create ideas of how things work around them (Thomas, 2017). Although Piaget did not discard social interaction, his goal was to highlight the "development of cognitive structures in learners" (Schcolnik et al., 2006, p. 13).

As a social constructivist, Vygotsky believed that learning takes place by collaborating with others and interacting with the environment (Schcolnik et al., 2006). James (2006), Pattalitan (2016), and Mercer et al. (1994) discuss Vygotsky's zone of proximal development. Mercer, et al. (1994) state that "[t]he zone refers to the instructional area between where the learner has independence (mastery) and what can be achieved with competent assistance (potential)" (p. 292).

Although constructivists may disagree about the amount of help that the instructor should offer the student, there are several similar teaching techniques which include, "modeling cognitive processes, providing guided instruction, encouraging reflection about thinking, giving feedback, and encouraging transfer" (Mercer, Jordon & Miller 1994, p. 292). James (2006) also indicates that formative assessments are likewise connected to the constructivist learning theory. Nagowah, L. and Nagowah, S. (2009) indicate that a strength of constructivist theory is that the students are able to problem solve more easily when an issue similar to a problem in their past arises; however, the weakness of the theory is when there is an expectation for all students to be similar in their thinking and the student needs to provide a response. In the constructivist theory, Mercer et al. (1994) state that assessments should be given before starting a lesson since teaching occurs inside what Vygotsky refers to as the zone of proximal development.

Connectivism. Although the most widely known learning theories are behaviorism, constructivism, and cognitivism, they were developed before there was extensive use of technology (Siemens, 2004). Connectivist theorists recommend a new method of acquiring knowledge (AlDahdouh, Osorio, & Caires, 2015). "Connectivism is a theoretical framework for understanding learning" (Kop & Hill 2008, p. 1). Siemens and Downes are the two people who first developed the digital age learning theory named connectivism (Duke, Harper and Johnston, 2013). The belief within this learning theory contends that huge changes are occurring in how students acquire knowledge, and a new theory needs to be added since you cannot build on the prior three theories (AlDahdouh, et al. 2015). Kop and Hill (2008) disagree with that thought and believe that this theory does not abandon the prior learning theories but builds on them since there are new occurrences that cannot be supported by the prior learning theories. This theory, discussed by Foroughi (2015), is a possible model in the way educators teach and students learn as technology advances and, as indicated by AlDahdouh, Osorio, Caires (2015), technology usage increases in the classroom setting.

A fundamental part of acquiring knowledge in connectivism is the students' ability to construct conclusions on the information that has been gathered (Kop & Hill 2008). Students need to have knowledge of how to find information, on a consistent basis, that supports and enhances their knowledge (Foroughi, 2015). "Connectivism presents a model of learning that acknowledges the tectonic shifts in society where learning is no longer an internal, individualistic activity"(Siemens 2004, p. 6). With the evolution of digital technology, the evolution of learning will also occur (Foroughi, 2015). Although Siemens and Downes indicate that connectivism is a new learning theory, Duke et al. (2013) point out that the prior three learning theories actually encompass all of the ideas of this theory and write about the possibility that this may actually be an instructional theory instead.

Formative and Summative Assessments

School district administrators and "policy makers" use the data collected from student evaluations to determine the strengths and shortcomings in the learners and school outcomes, and also to enhance instruction and how learners acquire knowledge (Looney, 2011, p. 5). Some of the data that school districts might use are formative or summative assessment results. Scriven (1967), as cited by Shuichi (2016), was the first person to investigate the roles of formative and summative assessments as it related to curriculum assessment; however, Shuichi (2016) also cited Bloom (1969) who expanded on Scriven's thoughts and included teaching into the explanation. Additionally, Taras (2005) indicates that formative and summative assessments both have similar procedures since they are both taking into account decisions made on "standards, goals and criteria" (p. 468).

Formative assessments. Historically, formative assessment has been referred to as "assessment for learning" (Hoover & Abrams, 2013, p. 219). It allows the instructor to offer comments to the learners on how they are acquiring knowledge, helps guide the learner in how to sustain and enhance their growth (Pattalitan, 2016), and it can also provide positive transformations in the classroom setting (Brookhart, 2004). According to Dixson and Worrell (2016), the purpose of formative assessment is to enhance instruction, student acquisition of knowledge, and to identify areas of weaknesses for the student. Formative assessment is also a method for educators to tailor their instruction to help lessen the space between where the student is currently achieving and the goal of where they should be achieving (Nichols, Meyers, & Burling, 2009). Stiggins (2002), as cited by Ghaicha (2016), states that formative assessments are more successful than summative assessments in motivating students.

Summative assessments. According to Stiggins (2004), as cited by Hoover and Abrams (2013), summative assessment can be described as "assessment of learning" (p. 220). Educators use summative assessments at the culmination of an interval of instruction to determine how much knowledge a student has acquired (Kibble, 2017). Dixson and Worrell (2016) indicated that the purpose of summative assessment is to assess how much knowledge students have acquired as well as making recommendations for future placements. Although state mandated assessments are one type of summative assessments that people think of when they hear the term summative assessment, Garrison and Ehringhaus, (2007) provide the following list of the various types of potential summative assessments:

- State assessments

- District benchmark or interim assessments
- End-of-unit or chapter tests
- End-of-term or semester exams
- Scores that are used for accountability for schools (AYP) and students (report card grades). (p. 1)

Whether students are completing a formative or summative assessment, it is important that the assessment is valid and reliable. Having an understanding of the psychometrics behind test development is one way to provide that understanding.

Psychometrics

When conducting a quantitative research study, it is important to look at psychometrics to gain an understanding about how the assessment is being researched. Standardized educational assessments are not new to education. According to Feuer (2011), "standardized educational tests have been a staple of public accountability in education for almost two centuries" (p. 26). As a historical perspective, in the final portion of the 19th century, psychometrics, as written by Merenda (2003), can be considered an extension of psycho-physics. Rosenkoetter and Tate (2017) define psychometrics as "the measurement of all kinds of phenomena of human experience" (p. 103). Adding to that definition, Hodges (2013), indicates that psychometrics is the ability to create numbers out of human phenomena.

As noted throughout research, there are assessment characteristics that are considered standard. Rust and Golombok (2009), (as cited by Rosenkoetter and Tate, 2017, p. 103), discuss the common characteristics of assessments. These characteristics include reliability, validity, standardization, and being bias free. Expanding on this concept, Hodges (2013) indicates that reliability is being able to transform the human phenomenon to a number in an accurate manner and validity is shown when that number remains consistent over time. DiBello and Stout (2007) state that “a valid test must be reliable;” however, reliability does not necessarily mean that a test is valid (p. 139). Using the information gathered by using psychometrics, researchers have made predictions on how students may perform on different assessments.

Predictive Analytics

Predicting how schoolchildren perform using analytic tools is growing in colleges, and experts in the field indicate that there is also great potential in the K-12 realm (Sparks, 2011). “The field of predictive analytics — using data to predict future events — is growing in popularity well beyond education” (Soland, 2014, p. 64). Although analyzing huge sets of data has been used in the fields of finance and physics, it is beginning to reach into the educational setting (Sparks, 2011). Analyzing data may potentially have a different endpoint depending on what field of study is conducting the analysis. In the field of investments, the prediction based on the predictive analytics, is the beginning and the endpoint; however, the prediction in education is the starting point of determining at risk students (Soland, 2014). Over the years, there have been original applications presented that touch every phase of the evaluation procedure: “knowledge base management, development of test items, computer delivery, and automated scoring” (Musso, 2009, p. 135). A variety of statistical approaches have been used in predictive analytics that help forecast the probability of a particular outcome (Sparks, 2011). “The data is processed using a collection of machine learning algorithms” (Blikstein & Worsley, 2016 p. 223). Using accessible information, data analysis should be able to predict the results that most accurately portrays the learner’s present learning level (Musso, 2009). Since researchers need a large quantity of data sets to acquire substantial conclusions, data had not been investigated to a great extent prior to the last several years (Sparks, 2011). In order to analyze data it will need to be stored in a central location with the ability to analyze it using a variety of queries.

Data Warehouse and Data Mining

Paré and Elovitz (2005) define a data warehouse as using a digital system to collect and store important information about the school district in one place that can be retrieved using specific queries. Adding to Paré and Elovitz’s definition, Han, Kamber and Pei (2012) indicate that institutions accumulate various data and preserve enormous databanks from numerous, diverse, and independent data sources. Starting around the year 2005, maintaining and collecting data electronically has shown significant growth (Erdongan & Timor, 2005). Although collecting and analyzing large amounts of data in education started to increase in 2008 when an international conference was held about this topic, data had been collected in other fields such as business and science for some time prior to that (Sparks, 2011). As cited by Iwantani (2018), Witten, Frank and Hall (2011) define data mining as “a process of systematically and automatically or semi-automatically, uncovering patterns in data” (p. 1). “New data collection and sensing technologies are making it possible to capture massive amounts of data in all fields of human activity” (Blikstein, & Worsley, 2016 p. 222).

Utilizing information that has been typically collected from schools in the past, educational data mining is starting to investigate learning in greater depth (Sparks, 2011).

Using data mining, there is a potential for educators to discover concealed or unspecified information that may be beneficial to them (Erdogan & Timor, 2005). Sparks (2011) raised a few questions about data collection and wondered if scholars could develop instruments for educators that could accumulate information like some online merchants currently do when they analyze the purchasers'spending behaviors. Educators can use the information generated by data mining to help drive their instruction. Using the process of data driven decision making (DDDM) is one possible way.

Data Driven Decision Making (DDDM)

Rallis and MacMullen (2000), as cited by Dunn, Airola, Lo, and Garrison (2013), indicated that data driven decision making (DDDM) is a student focused instructional instrument with an emphasis on offering information to educators that will allow them to make appropriate modifications to their lessons to provide for student educational needs. "DDDM focuses on the use of data, statistical analysis, and explanatory and predictive models to gain insights, and inform policies around complex issues" (Buschel, 2012 in Dejear Jr., Yu, DuBois Baber, & Li, 2018, p. 43). Educators have different ability levels when they are analyzing data and some of them may feel ill-equipped at the task (Datnow and Hubbard, 2016). The school district should provide extra professional development to educators who are not comfortable using data driven decision making strategies to drive their instruction. Educators use the information gathered from the data analysis to decide what type of supports each student may require (Dunn, Airola, Lo, & Garrison, 2013). When an educator is using data to make decisions about student learning needs, they should not confine their data analysis to only test data, but also look at a variety of other information they have gathered on the students' ability to acquire knowledge so that they can make a more informed analysis to drive their instruction (Datnow & Hubbard, 2016). Utilizing the DDDM strategy, educators can differentiate their lessons to meet the learning needs of the students in their classroom.

Summary

Since the passage of the Elementary and Secondary Education Act of 1965 (ESEA) and its latest reauthorization, the Every Student Succeeds Act of 2015 (ESSA), the federal government has made education a priority. Through the many reauthorizations, Congress has tried to enhance each state's ability to improve education for all students. The latest reauthorization gives states more control over assessment.

Assessment and learning theories provide the backdrop for academic progress. Based on the four types of learning theories it is apparent that each learning theory has its own beliefs on how learning occurs and how students should be assessed. However, formative assessment was highlighted in both the cognitivism and constructivism theories.

Educational assessments are used for many different reasons. They can be formative or summative. The main goal of any educational assessment is to foster student achievement. Formative assessments provide information on the knowledge that a student currently knows. Summative assessments gives the instructor information about what a student has mastered at the end of a unit of instruction.

School districts have started to store data in a data warehouse. By analyzing this information, school districts are able to run queries to have a better understanding on how each student is progressing academically. Using information gathered from a data warehouse, school districts have the ability to use data in a variety of ways. Utilizing the data that is gathered is valuable for educators to help plan instruction materials that would increase student learning.

A quasi-experimental methodology design was used to study the LinkIt!© mathematics assessment as a predictor of how well a student will score on the PARCC mathematics assessment.

Based on the literature review the following research questions are addressed in this research study:

Research Questions

1. What is the accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period?

Null Hypothesis: There will be no difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period.

Alternative Hypothesis: There will be a difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period.

2. When comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score, what differences in accuracy rates are revealed over the two-year period for each of the three forms, based on groupings of students in:
    - general education,
    - special education, and

- gifted and talented education?

Null Hypothesis: When looking at sub-groups of students, there will be no statistically significant difference in accuracy rates over the two-year period for each of the three forms based on groupings of students in general education, special education, and gifted and talented education when comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score.

Alternative Hypothesis: When looking at sub-groups of students, there will be a statistically significant difference in accuracy rates over the two-year period for each of the three forms based on groupings of students in general education, special education, and gifted and talented education when comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score.

3. What is the relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score?

Null Hypothesis: There will be no statistically significant relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score.

Alternative Hypothesis: There will be a statistically significant relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score.

4. What is the accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period by grade level?

Null Hypothesis: There will be no difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period by grade level.

Alternative Hypothesis: There will be a difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period by grade level.

Chapter Three: Methodology

Introduction

With the introduction of the Partnership for Assessment of Readiness for College and Careers (PARCC) assessment in New Jersey, various stakeholder groups tried to resist the implementation. Parents formed groups to protect and "opt" their children out of testing; students spoke with the State Board of Education to relay the stress of the new assessment, teachers were concerned that their evaluation ratings would be lower since the PARCC scores will be used as part of their evaluation system, and several school districts did not meet the 95% participation threshold. Since the 2015 Every Student Succeeds Act (ESSA) requires students to complete a yearly assessment in grades three through eight as well as one time in high school (Skinner & Kuenzi, 2015), school district leaders need to find a way to help all of the students in the district progress. Using a formative assessment tool that can help predict the state mandated assessment score could help fill the need.

States have the freedom to determine what state assessment they will use to meet the mandates of the 2001 NCLB and the 2015 ESSA assessment requirements. Based on information gathered from State of New Jersey website, the Department of Education designated that the students in this state during the period of time covered by the study would take the Partnership for Assessment of Readiness for College and Careers (PARCC) assessment (https://www.state.nj.us/education/archive/assessment/20162017TestingCalendar.pdf). This assessment is delivered as an online or paper and pencil assessment depending on the needs of the student. Pearson is the contract provider of the Partnership for Assessment of Readiness for College and Careers (PARCC) assessment.

These mandated summative assessments set the stage for school districts to find ways to support student success on the assessments. One direction that school districts may pursue is to purchase commercial preparation materials that could provide formative assessment information, which would help teachers find the learning gaps for the students in their classrooms. One such assessment tool is LinkIt!©, a data warehousing, assessment solutions and analytics platform. Based on the student results of the three forms of the LinkIt!© assessments, as part of the LinkIt!© Navigator report, the company provides a predictive measure of how a student might perform on the state mandated assessment; in this research study, the PARCC assessment.

LinkIt!© is a computerized assessment tool that school districts can purchase to administer assessments and use the data to drive instruction. LinkIt!© has developed their assessments, using a computerized testing platform or paper and pencil format, to be similar to the PARCC assessment platform. The online tools that are used in the LinkIt!© platform emulate the online tools that are used on the PARCC assessment. According to the New Jersey 2019-2020 Data Warehousing, Assessment Solutions and Analytics catalogue, along with the three benchmark assessments, Form A, Form B, and Form C, LinkIt!© also offers an option to purchase the use of Progress Monitors and Probes, K-8 Learning Library, Certica Navigate Item Bank and Progress Checks, Algebra Readiness and LinkIt!© Prime, which allows school staff to upload tests and answer keys in word or PDF format (p. 223).

Although LinkIt!© offers a plethora of options in their reporting, this research study looked at LinkIt!©'s mathematics assessment score band PARCC predictive accuracy on the actual PARCC mathematics assessment score band. The following research questions were used to determine the predictive accuracy of the three LinkIt!© forms and the actual PARCC assessment results.

Research Questions

1. What is the accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period?

Null Hypothesis: There will be no difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period.

Alternative Hypothesis: There will be a difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period.

2. When comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score, what differences in accuracy rates are revealed over the two-year period for each of the three forms, based on groupings of students in:

    - general education,
    - special education, and
    - gifted and talented education?

Null Hypothesis: When looking at sub-groups of students, there will be no statistically significant difference in accuracy rates over the two-year period for each of the three forms based on groupings of students in general education, special education, and gifted and talented education when comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score.

Alternative Hypothesis: When looking at sub-groups of students, there will be a statistically significant difference in accuracy rates over the two-year period for each of the three forms based on groupings of students in general education, special education, and gifted and talented education when comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score.

3. What is the relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score?

Null Hypothesis: There will be no statistically significant relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score.

Alternative Hypothesis: There will be a statistically significant relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score.

4. What is the accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period by grade level?

Null Hypothesis: There will be no difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period by grade level.

Alternative Hypothesis: There will be a difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period by grade level.

Setting

The research study was conducted in a rural elementary school in central New Jersey. Based on information gathered from the New Jersey Department of Education website, in 1975, New Jersey developed a method, District Factor Groups (DFG), which allows the state to compare how students were performing on the state assessments based on districts who were similar demographically (https://www.nj.gov/education/finance/rda/dfg.shtml). This method was developed using census information from the Census Bureau and is updated every 10 years when the Decennial Census data is released. This measurement is based on the socioeconomic status (SES) of the community. The rating scale starts with A and ends with J. Districts with an A designation are the lower socio- economic schools and districts with the J designation are the higher socio-economic schools. Based on the New Jersey Department of Education's District Factor Group (DFG) rating scale, the district in this study is considered a District Factor Group I school. The racial demographics of this DFG I school were over 80% white in both years of the research study.

Subjects

The data collected for this study were the score bands for third through eighth grade students during the 2016-2017 and 2017-2108 school years in the elementary school studied. Based on data gathered from the participating school district, the research study sample size ranged from 211 to 219 subjects. The total number (n) for each of the qualifying data points from the LinkIt!© mathematics assessment forms is shown in Table 1. The sample was further divided into three subgroups: general education, special education, and gifted and talented. Table 2 indicates the subgroup participation sample for each of the six LinkIt!© mathematics assessment forms.

Table 1

Students Enrolled in Each Grade Level

Grade Level	2016-2017			2017-2018		
Grade 3	Form A n=21	Form B n=21	Form C n=21	Form A n=36	Form B n=36	Form C n=36
Grade 4	Form A n=31	Form B n=31	Form C n=32	Form A n=26	Form B n=27	Form C n=27
Grade 5	Form A n=38	Form B n=38	Form C n=38	Form A n=28	Form B n=28	Form C n=28
Grade 6	Form A n=41	Form B n=41	Form C n=41	Form A n=39	Form B n=39	Form C n=40
Grade 7	Form A n=42	Form B n=43	Form C n=41	Form A n=38	Form B n=37	Form C n=38
Grade 8	Form A n=44	Form B n=45	Form C n=44	Form A n=44	Form B n=44	Form C n=44
Total	217	219	217	211	211	213

The data were selected based on meeting the following criteria requirements: the sample was drawn from the score bands of students in third through eighth grade enrolled on the date that the assessment was administered and who also took at least one of the LinkIt!© mathematics assessment forms and also took the PARCC mathematics assessment during either of the two assessment years. Since the score bands of every student were selected based on meeting the research criteria, nonprobability sampling was used since there is not an equal chance for every student's score band to be considered if they did not meet the selection criteria.

Table 2

Sub Group Population Count

Sub Group	2016-2017			2017-2018		
General Education Students	Form A n=130	Form B n=131	Form C n=129	Form A n=125	Form B n=125	Form C n=127
Special Education Students	Form A n=42	Form B n=43	Form C n=43	Form A n=43	Form B n=43	Form C n=43
Gifted and Talented	Form A n=47	Form B n=47	Form C n=47	Form A n=47	Form B n=47	Form C n=47

This study was conducted by reviewing the LinkIt!© predictive PARCC mathematics assessment score band for all three of the LinkIt!© mathematics assessment forms and the PARCC mathematics assessment score band results. Data for students in the third through eighth grade classrooms as well as for small group pullout classrooms for special education students during the 2016-2017 and the 2017-2018 school years were included in this study.

Student data were disaggregated in several ways. Data was looked at for the total population of students as well as breaking the data down into three sub groups. The three sub-groups that were analyzed were general education students, special education students (this data includes students with an Individualized Education Plan (IEP), and students with a 504 plan), and gifted and talented students. When looking at the special education data, students with a speech only Individualized Education Plan (IEP) were also be calculated with the special education students. Since the populations of some of these sub-groups is smaller in number, all of the subgroups will be calculated as a total number of students as opposed to grade level.

Instruments

LinkIt!© Assessment. LinkIt!©, a commercially produced formative assessment tool, was administered three times during the school year. Form A of the assessment was administered in September, Form B of the assessment wsasadministered in January, and Form C of the assessment was administered in May. Testing is flexible depending on when the school district would like to set the dates. The school district being researched for this study used the multiple-choice form of the LinkIt!© assessment during these assessment years. The school district switched to the technology-enhanced version during the 2018-2019 school year. The students then completed the assessment using the computer-based format.

The LinkIt!© assessment was administered at various points of time during the school day depending on when the students had mathematics instruction. Typically, the students started the assessment during the mathematics class and could finish it at a later point during the day if they needed more time. The LinkIt!© assessment takes approximately sixty minutes to complete, but students are allotted extra time, without penalty, to finish if it is needed.

Although this research study used only the predictability assessment results of the LinkIt!© Form A, Form B, and Form C mathematics assessments in relationship to the actual outcomes of the PARCC mathematics assessment for the years being studied, LinkIt!© also provided sub scale scores for their assessments. According to the LinkIt!© New Jersey 2019-2020 Data Warehousing, Assessment Solutions and Analytics catalogue, school districts who use LinkIt!© are able to create on demand assessment reports. These reports include information on the following sub score: standards, topics, skills, and item analysis. The standards are based on the state that is using the LinkIt!© platform. LinkIt!© is able to disaggregate information for each school based on their state standards. The LinkIt!© platform on demand reports can also break out the testing information by topics and skills and can also let the teacher know what questions were in those areas. The reports can also let the teacher know where there are skill gaps that need to be addressed. By disaggregating the LinkIt!© assessment information, teachers are able to determine weaknesses in the skill areas of each student. By using this information throughout the school year, the teacher is able to differentiate for each student based on individual needs to strengthen the skill deficits.

When making the PARCC mathematics assessment prediction, LinkIt!© uses six areas that a student could score on the PARCC assessment. LinkIt!© uses the following six areas: Not Meeting, Partially Meeting, Approaching, Bubble, Meeting, and Exceeding. LinkIt!©'s added measure of *Bubble* is for students who may score in either the Approaching or Meeting area of the PARCC assessment. Although there are other educational considerations to keep in mind, this category might help indicate to the school district that these students have the potential to score in either the lower or higher area.

LinkIt!© uses a percentage band to help determine which level of expectations a student may fall in. These percentage bands change for each form of the assessment. This allows the company to make predications on how the student may score on the PARCC mathematics assessment. Although school districts who subscribe to the LinkIt!© platform are able to view the percentage bands, LinkIt!© has not published publicly their percentage band cutoffs.

LinkIt!© validity and reliability. Based on the LinkIt!© technical report, the company uses a statistical process to review the item validity of the assessment items. LinkIt!© calculates item validity using the "point biserial correlation coefficient" (p. 1). The following information is a summary of the technical report on biserial correlation. This measure looks at the correlation between the performance on an assessment item and the performance on the complete assessment. The range of the point biserial correlation coefficient is between -1.00 and +1.00. Test items that have a positive biserial inform the test developers that students who scored high on the assessment most likely would answer a test item correctly. On the other hand, a negative biserial correlation informs the test developers that students who scored high on the assessment got that test item wrong more often than students who scored low on the assessment. If a negative biserial result occurs, test developers realize that there is a flaw in their question construction (LinkIt!© Technical Report, p. 1).

According to the LinkIt!© technical report, test developers desire a +0.30 in a point biserial correlation coefficient. If a test item is below +0.30 LinkIt!©'s test developers will review that question. LinkIt!© uses a range of difficulty (relatively easy to difficult) in their assessments.

The LinkIt!© technical report also discusses predictive validity. LinkIt!© defines predictive validity as "forecasting performance on future assessments" (p. 3). The company uses a regression analysis when comparing a group of students who took the same LinkIt!© assessment and the state mandated assessment. LinkIt!© uses the PARCC assessment for New Jersey students. However, the technical report indicates that they can apply this strategy to any state mandated assessment. In order for LinkIt!© to provide the predictive reports, students need to have gone through a cycle of benchmark assessments, such as the LinkIt!© Form A, Form B, or Form C and have also completed a summative assessment, typically the state mandated assessment. Using the relationship between the two data points, LinkIt!© derives a correlation for the next time the student takes the state mandated summative assessment and makes a prediction on how the students may score.

In order to gauge the reliability of the assessment, the technical report indicates that LinkIt!© uses a Cronbach Alpha Coefficient formula. This formula calculates the "internal consistency reliability by determining how all items on a test relate to all other test items and to the total test" (Mills & Gay, 2016, p. 175), in other words, how well the subject area is measured by the assessment. The technical report explains that if the construct is broad, the assessment is less reliable. The number of items tested and the extensiveness of the construct assessed can affect the Cronbach Alpha Coefficient formula. Having more than twenty assessment items helps to make the formula more appropriate.

LinkIt!©'s technical report states there are three significant variables of the Cronbach's formula. LinkIt!©'s report indicates that these three variables include: "(1) the number of test items on the exam; (2) student performance on every test item; and (3) the variance (standard deviation squared) for the set of student test scores" (p. 4). The range of the index for the Cronbach Alpha is 0.00 to 1.00. A highly unreliable value would be close to the 0.00 mark. The technical report indicates that an assessment is reliable when it has a high Alpha value (LinkIt!©'s Technical Report p. 4).

PARCC assessment. The State of New Jersey allows a flexible schedule for administration of the PARCC assessment during the months of April and May, based on the assessment calendar distributed by the State Department of Education Office of Assessment. The school district being researched administered the assessment over several days during the months of April and May for both of the assessment years of this study. New Jersey allocates a particular timeframe that the state mandated assessments must be completed by in each school district. In the 2016-2017 PARCC assessment schedule, the State of New Jersey designated March 27th to May 19th as the testing window for the PARCC assessment. The State of New Jersey allowed each school district to pick a 30-day period for all of the assessment to be completed. In the 2017-2018 PARCC assessment schedule, the State of New Jersey designated April 16th to May 25th as the PARCC testing timeframe. All of the students started testing at the same time for the allotted minutes allowed by the testing protocol.

In the research study school, the PARCC assessment was administered in the morning beginning at 9:00 AM. The allocated time for the mathematics PARCC assessment varies depending on the grade levels being assessed. The PARCC administration manual indicates all of the directions for the teacher to follow to keep the administration consistent from classroom to classroom. Students in the general education population are given a set amount of time to complete each section of the PARCC mathematics assessment.

The testing times do not include the time needed to hand out or collect materials and read the directions. For the years being researched for this study, testing for grades three through five was conducted over a four-day period, and testing for grades six through eight was conducted over a three-day period. Students with an Individualized Educational Plan (IEP), a 504 plan, or students who are English Language Learning (ELL) eligible may be allotted extra time to complete the assessment depending on what modifications are written in their Individualized Education Plan (IEP), 504 plan, or ELL plan. Based on the PARCC Administration Manual during the 2016-2017 and 2017-2018 school years, students in third through eighth grade were given the following amount of time to complete the PARCC mathematics assessment (see Table 3).

Table 3

Amount of Time Allocated for the PARCC Assessment for the 2016-1017 and 2017-2018 school years

Mathematics	Unit 1	Unit 2	Unit 3	Unit 4	Total Time
Grades 3-5	60 mins.	60 mins.	60 mins.	60 mins.	4 hours
Grades 6-8	80 mins.	80 mins.	80 mins.	NA	4 hours
Algebra I	90 mins.	90 mins.	90 mins.	NA	4 hours 30 minutes

The PARCC assessment, based on information gathered from the website http://understandthescore.org/score-report-guide/, in the mathematics assessment area, is broken down into four main areas. These areas, Major Content, Expressing Mathematical Reasoning, Additional & Supporting Content, and Modeling and Application, give the teachers and parents some information about what was being assessed for the grade level on the PARCC assessment. Based on information taken from the sample score report from the Spring 2017 PARCC Score Report listed on the understandingthescore.org website, the

following topics are assessed in the four sub groups for each grade level: (http://www.understandthescore.org/wp-content/uploads/2017/08/New-Jersey.compressed.pdf)

- Major Content –

  Grade 3 – "Students meet expectations by solving problems involving multiplication and division, area, measurement, and basic fraction understanding" (p. 20)

  Grade 4 – "Students meet expectations by solving problems involving addition, subtraction, multiplication and division, place value, fraction comparisons, and addition and subtraction of fractions with same denominators" (p. 22)

  Grade 5 – "Students meet expectations by solving problems involving volume of prisms, adding, subtracting, multiplying and dividing with multi-digit whole numbers, decimals, and fractions" (p. 24)

Grade 6 – "Students meet expectations by solving problems involving ratios, rates, percentages, an understanding of negative numbers, graphing points and simple linear functions, linear expressions, and linear equations" (p. 26)

Grade 7 – "Students meet expectations by solving problems involving proportional relationships, adding, subtracting, multiplying and dividing with rational numbers, and linear expressions, equations, and inequalities" (p. 28)

Grade 8 – "Students meet expectations by solving problems involving radicals, exponents, scientific notation, linear equations, systems of linear equations, linear and nonlinear functions, the Pythagorean Theorem, and transforming shapes on a coordinate plane" (p. 30)

Algebra 1 – "Students meet expectations by solving problems involving arithmetic operations on polynomials, linear, quadratic, and exponential equations, an understanding of functions, and interpreting algebraic expressions, functions, and linear models" (p. 32)

- Expressing Mathematical Reasoning –

  Grade 3 – "Students meet expectations by creating and justifying logical mathematical solutions and analyzing and correcting the reasoning of others" (p. 20)

  Grade 4 – "Students meet expectations by creating and justifying logical mathematical solutions and analyzing and correcting the reasoning of others" (p. 22)

Grade 5 – "Students meet expectations by creating and justifying logical mathematical solutions and analyzing and correcting the reasoning of others" (p.24)

Grade 6 – "Students meet expectations by creating and justifying logical mathematical solutions and analyzing and correcting the reasoning of others" (p. 26)

Grade 7 – "Students meet expectations by creating and justifying logical mathematical solutions and analyzing and correcting the reasoning of others" (p. 28)

Grade 8 – "Students meet expectations by creating and justifying logical mathematical solutions and analyzing and correcting the reasoning of others" (p. 30)

Algebra 1 – "Students meet expectations by creating and justifying logical mathematical solutions and analyzing and correcting the reasoning of others" (p. 32)

- Additional & Supporting Content –

  Grade 3 – "Students meet expectations by solving problems involving perimeter, place value, geometric shapes, and representations of data" (p. 20)

  Grade 4 – "Students meet expectations by solving problems involving number and shape patterns, simple measurement conversions, angle measurements, geometric shapes classification, and representations of data" (p. 22)

Grade 5 – “Students meet expectations by solving problems involving writing and interpreting numerical expressions, converting measurements, graphing points, classifying geometric shapes, and representing data” (p. 24)

Grade 6 – “Students meet expectations by solving problems involving area, volume, and statistics” (p. 26)

Grade 7 – “Students meet expectations by solving problems involving circumference, area, surface area, volume, statistics, and probability” (p. 28)

Grade 8 – “Students meet expectations by solving problems involving irrational numbers, volume, and scatter plots” (p. 30)

Algebra 1 – “Students meet expectations by solving problems involving properties of rational and irrational numbers, writing algebraic expressions in equivalent forms, systems of equations, interpreting data, and linear, quadratic, and exponential models” (p. 32)

- Modeling & Application –

  Grade 3 – “Students meet expectations by solving real world problems, representing and solving problems with symbols, reasoning quantitatively, and strategically using appropriate tools” (p. 20)

  Grade 4 – “Students meet expectations by solving real-world problems, representing and solving problems with symbols, reasoning quantitatively, and strategically using appropriate tools” (p. 22)

Grade 5 – "Students meet expectations by solving real-world problems, representing and solving problems with symbols, reasoning quantitatively, and strategically using appropriate tools" (p. 24)

Grade 6 – "Students meet expectations by solving real-world problems, representing and solving problems with symbols, reasoning quantitatively, and strategically using appropriate tools" (p. 26)

Grade 7 – "Students meet expectations by solving real-world problems, representing and solving problems with symbols, reasoning quantitatively, and strategically using appropriate tools" (p. 28)

Grade 8 – "Students meet expectations by solving real-world problems, representing and solving problems with symbols, reasoning quantitatively, and strategically using appropriate tools" (p. 30)

Algebra 1 – "Students meet expectations by solving real-world problems, representing and solving problems with symbols, reasoning quantitatively, and strategically using appropriate tools" (p. 32).

The PARCC assessment uses five areas that a student could score on the mathematics assessment. PARCC uses the following five areas: Did Not Yet Meet Expectations, Partially Met Expectations, Approached Expectations, Met Expectations, and Exceeded Expectations. Scoring in the Met Expectations and Exceeded Expectations would indicate that the student scored in the expected grade level range.

PARCC also has cutoff points for each of their score areas. Based on the 2016 Score Interpretation Guide from Pearson, the score ranges for grades three through eight are shown in Table 4.

Table 4

PARCC Grade Level Cutoff Ranges for the 2016-2017 and 2017-2018 Testing Years

Grade Level	Did Not Yet Meet Expectations	Partially Met Expectations	Approached Expectations	Met Expectations	Exceeded Expectations
Grade 3	650-699	700-724	725-749	750-789	790-850
Grade 4	650-699	700-724	725-749	750-795	796-850
Grade 5	650-699	700-724	725-749	750-789	790-850
Grade 6	650-699	700-724	725-749	750-787	788-850
Grade 7	650-699	700-724	725-749	750-785	786-850
Grade 8	650-699	700-724	725-749	750-800	801-850
Algebra I	650-699	700-724	725-749	750-804	805-850

PARCC validity and reliability. The PARCC 2017 Technical Report details the steps taken by Pearson, the product vendor, for the PARCC assessment. The Report states that validity is an ongoing process that helps to validate the interpretations of the assessment scores for various uses (p. 135). Pearson used the 2016-2017 assessment to collect verification of validity, or the lack thereof (PARCC 2017 Technical Report, 2018 p. 135). There were two areas that were looked at for validity in the Technical Report. These areas are: Evidence Based on Test Content and Evidence Based on Internal Structure (PARCC 2017 Technical Report, 2018 p. 135).

Evidence Based on Test Content looks at the level of agreement involving the test items and content standards (PARCC 2017 Technical Report, 2018). "The PARCC assessment adheres to the principle of evidence-centered design" (PARCC 2017 Technical Report, 2018, p. 135). Evidence centered design looks at the standards that are being assessed and how the student needs to perform to reach that standard (PARCC 2017 Technical Report, 2018). This criteria is indicated in the evidence statements for the PARCC assessment. The 2017 Technical Report also indicates that performance level indicators are also used to align the content (p. 136). Construct validity evidence, as indicated in the Report, is engrained in the development and validation process of the PARCC assessment (p. 136). Many stakeholders were involved in the process of developing the assessment (PARCC 2017 Technical Report, 2018, p. 13). Pearson also "conducted research studies to validate the PARCC item and task development approach" (PARCC 2017 Technical Report, 2018, p. 136).

In 2014, Pearson used a field test prior to the full implementation of the PARCC assessment. Information was gathered from the teachers, students (PARCC 2017 Technical Report, 2018, p. 136). The Report indicated that this feedback looked at the students experience and the quality of the assessment items (p. 136). During the construction of the PARCC assessment, Pearson also kept construct-irrelevant variance in mind (PARCC 2017 Technical Report, 2018, p. 136). If an item fell into this category, in order to be fair to all of the subgroups, these items should not be part of the PARCC assessment question bank (PARCC 2017 Technical Report, 2018, p. 137).

The area of Evidence Based on Internal Structure looks at the relationship between the "test items and/or test components" to try and find the extent the items and/or components indicate the construct that an interpretation for a test score can be based (PARCC 2017 Technical Report, 2018, p.137). In the 2017 PARCC Report, construct is defined as "the characteristics that a test is intended to measure" (p. 137).

The PARCC 2017 Technical Report indicates that the "PARCC assessment provides a full summative test score….. for the mathematics sub claim scores" (p. 137). One of the goals of providing the summative score for the sub claim areas is for teachers to use the information to drive instruction. As indicated earlier, the PARCC mathematics assessment is broken out into four sub groups: Major Content, Mathematical Reasoning, Modeling Practice and Additional and Supporting Content (PARCC 2017 Technical Report, 2018 p. 138). Validity can be further evidenced when there is a "high total group internal consistencies as well as similar reliabilities across subgroups" (PARCC 2017 Technical Report, 2018, p. 138).

Based on the PARCC 2017 Technical Report, there are several measures used to test for reliability. In the section: Raw Score Reliability Estimations, similar to the LinkIt!© assessment, the PARCC assessment also uses the Cronbach Alpha Coefficient formula to measure the internal consistency reliability (PARCC 2017 Technical Report, 2018, p. 94). As indicated earlier, the internal consistency reliability is higher when there are more items included in the test (PARCC 2017 Technical Report, 2018, p. 94). The PARCC assessment has different item types which may measure a variety of skills, therefore, the stratified alpha formula is used. According to the PARCC 2017 Technical Report, this formula separates the assessment into different parts, computes the alpha for each of the parts, then uses the "results to estimate the reliability coefficient for the total score" (p. 94).

In the next section of the report, Scale Score Reliability Estimation, the 2017 Technical Report indicates that it is not possible to use the stratified alpha coefficient since the scale score is based on a total score and not separate items within the test; for that reason, the PARCC assessment used the scale score reliability from Kolen, Zeng and Hanson (1996) (p. 95). “Scale score reliability coefficients range from 0 to 1” (PARCC 2017 Technical Report, 2018, p. 95). It is desirable to obtain a scale score closer to 1 since it is more likely that a student would score about the same on a repetitive assessment occurrence (PARCC 2017 Technical Report, 2018, p. 95).

The Reliability of Classification is another section that is discussed for reliability. The 2017 Technical Report indicates that the BB-CLASS computer program was used for reliability (p. 129). This computerized program approximates two kinds of statistics using the information gathered after the administration of the first assessment (PARCC 2017 Technical Report, 2018, p. 129). The two types of statistics are decision accuracy and decision consistency (PARCC 2017 Technical Report, 2018, p. 129). Decision accuracy, also known as classification accuracy, refers to the rate at which an individual assessment is classified into the correct classification category (Lathrop & Cheng, 2014). Decision consistency, also referred to as classification consistency, is when two non-overlapping forms of a test classify the test-taker into the same classification category on both assessments (Lathrop & Cheng, 2014).

Finally, in the reliability area, the PARCC 2017 Technical Report discusses the use of Inter-rater Agreement (p. 134). Inter-rater reliability looks at the correctness of the rating method (Wilhelm, Rouse, and Jones, 2018). Pearson uses the outcomes of the interrater reliability to determine if training or intervention needs to be conducted for the individual or the group as a whole (PARCC 2017 Technical Report, 2018, p. 134).

Design of the Study

The purpose of this quasi-experimental quantitative research study was to determine if there is a nexus between the accuracy of the predictive ability of the LinkIt!© mathematics assessment and the PARCC mathematics assessment score band results. Since LinkIt!© started providing predictive assessment data in the 2016-2017 school year, this research study looked at data from a two-year period, 2016- 2017 and 2017-2018, in one school in New Jersey.

This study looked at data from student scores administered on two types of assessments: the three LinkIt!© mathematics assessment forms as well as the PARCC mathematics assessment score results. Data gathered from the three LinkIt!© mathematics assessment forms and the PARCC mathematics assessment score band results were analyzed based on total population results as well as looking at three sub-groups of student populations (general education, special education, and gifted & talented). The study also looked to see if there is a relationship between the three LinkIt!© mathematics predictive score band results and the actual PARCC mathematics assessment score band results. Finally, the data were analyzed to determine accuracy rates based on grade levels. Data was used if it met the specified criteria for the testing year being analyzed.

Procedures

A letter was sent to the superintendent of the school of the study requesting permission to conduct the research study (see Appendix B). The letter invited the school district to participate in the research study. It indicated that the proposed study would be looking at LinkIt!© mathematics assessment and PARCC mathematics assessment data from the 2016-2017 and the 2017-2018 school years. The letter also indicated the potential research questions, data fields that would be required to conduct the research study, how the data would be coded, and an assurance of confidentiality. The school district followed up with a letter of response agreeing to participate in the research study (see Appendix C). An email was sent to the president of LinkIt!© requesting to use the LinkIt!© name and to use the information in the LinkIt!© catalogues. The president responded that the researcher was allowed to use both pieces of information requested. A second letter was sent to the superintendent of the school of the study to provide the finalized questions for the study. After Institutional Review Board approval (IRB), (see Appendix A), a second letter was sent to the superintendent of the school district in the study to inform him of the changes to the questions, the updated data fields that would be required to conduct the research study, and an assurance of confidentiality (see Appendix D). The school district provided a flash drive containing an Excel spreadsheet with the required data fields needed to complete the study.

Data Sources

Data sources for this research study include accuracy and prediction for the total school and grade level score band results from the LinkIt!© mathematics assessment Form A, Form B, and Form C along with the PARCC mathematics assessment score band results from the 2016-2017 and 2017-2108 school years for grades three through eight. This data also included the LinkIt!© predicted result for the PARCC mathematics assessment for each of the LinkIt!© mathematics assessment forms. Finally, the data included information about the three subgroups (general education, special education, and gifted and talented) being studied.

Data Analysis Summary

Using formative and summative assessment data, the research study examined four questions focusing on data from grades three through eight. For the purpose of this study, several research methods were used to analyze the data to answer the research questions. Descriptive statistics were run for both question one and question four. The descriptive statistics in question one were run to determine the accuracy of the LinkIt!© PARCC mathematics assessment prediction and the actual PARCC mathematics assessment result. Question four determined the accuracy rate for the three forms for each year of the study, of the LinkIt!© mathematics predictive assessment results in predicting actual PARCC mathematics assessment scores by grade level. A one way ANOVA was used for question two, to determine if there was a statistical difference in the accuracy rates of the predictive LinkIt!© mathematics assessment score band for each form based on the following three subgroups: general education, special education, and gifted and talented education. The number of scores is different for each subgroup, therefore, an ANOVA Sidak Post Hoc was run for each of the six LinkIt!© forms. Finally, a Pearson r correlation was run to investigate the relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score. A correlation is defined as “the relationship between two things” (Knapp, 2017, p. 183).

Chapter Four: Results

Introduction

The No Child Left Behind Act of 2001 (NCLB) required states to administer annual assessments to students in grades three through eight and also one time in high school. This mandate was continued through the Every Student Succeeds Act of 2015 (ESSA) reauthorization. School districts continue to look for ways to help the students in their district to perform well on state mandated summative assessments. One option districts have is to purchase a commercially produced formative assessment tool that would help predict how the student would score on the state mandated assessment.

The purpose of this quasi-experimental quantitative research study was to determine if there is a nexus between the accuracy of the score band predictive ability of the LinkIt!© mathematics assessment and the PARCC mathematics assessment score band results. This research study looked at LinkIt!© mathematics assessment score band and PARCC mathematics assessment score band data over a two year period, 2016-2017 and 2017-2018, in one elementary school in New Jersey. LinkIt!© is a commercially produced formative assessment tool that students in the school took three times during the school year (September, January and May). PARCC is a summative assessment tool that students took in the spring of the school year. Starting in the 2016-2017 school year, LinkIt!© added a PARCC score band predictive component. This predictive component indicates to the school district the potential score band a student might score on the PARCC assessment based on the outcome from the three different LinkIt!© form assessments. LinkIt!© makes a score band prediction after the completion of each form based on a scale score cutoff. Therefore, although this school district had been using the

LinkIt!© for several years prior to 2016-2017, this research study started with the 2016-2017 school year since that is when LinkIt!© started with the PARCC predictive component.

Data Analysis

This research study exclusively looked at data for students in grades three through eight who took the LinkIt!© mathematics assessments and PARCC mathematics assessment during the two years identified for the research study. Data gathered from the three LinkIt!© mathematics assessment forms PARCC predicted score band and the actual PARCC mathematics assessment score band results were analyzed. Participation criteria required students to take any of the LinkIt!© mathematics assessment forms as well as the PARCC mathematics assessment during at least one of the research study years. The research study looked at the LinkIt!© mathematics assessment PARCC predictive score band and the actual PARCC score band on both assessments. For the purpose of this research study, the term score will refer to a specific score band on the LinkIt!© mathematics assessments and PARCC mathematics assessments.

In the 2016-2017 school year, LinkIt!© started providing a PARCC predictive component to their Form A, B, and C Navigator results. This prediction helps guide school districts to the score band a student might score on the PARCC assessment. The criteria to determine predictability is based on scale scores (a percent) to create the cut off scores prediction score band. According to the president of LinkIt!©, the company also created a secondary, unofficial method, using raw scores. The raw scores are the number of questions that a student would need to get correct on each of the three forms for each of the score band achievement levels, to set their score band cutoff criteria (R. Winters, personal communication, October 14, 2019).

The data score range for LinkIt!© included the following six categories: Not Meeting, Partially Meeting, Approaching, Bubble, Meeting and Exceeding. PARCC used the following five categories: Did Not Yet Meet Expectations, Partially Met Expectations, Approached Expectations, Met Expectations and Exceeded Expectations. LinkIt!© adds the Bubble category to their assessment results indicating that a student may score on the approached expectations or met expectations range. The Bubble category is only used between the approached expectations and met expectations range. For the purpose of this study, if a student scored in the Bubble range and scored in either the approached expectation or met expectation range for the PARCC mathematics assessment their score band accuracy was considered correct. The research study investigated the accuracy of prediction of the LinkIt!© mathematics predictive assessment score band results in predicting actual PARCC mathematics assessment score band results for students in one elementary school over a two-year period.

Valid scores are based on the students who took one or more of the LinkIt!© mathematics assessment forms and also took the PARCC mathematics assessment during the same school year. Therefore, if a student missed taking an assessment form or moved into the school district after the administration of one of the forms, but took one or more of the LinkIt!© mathematics assessment forms and the PARCC mathematics assessment, the data were included in the study.

Research Question 1

What is the accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period?

To determine the accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one elementary school over a two-year period the following hypotheses were used:

Null Hypothesis: There will be no difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period.

Alternative Hypothesis: There will be a difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period.

Descriptive statistics were gathered to determine the rate of the LinkIt!© mathematics prediction accuracy on the PARCC mathematics assessment. The accuracy rate for the three LinkIt!© mathematics assessment forms for the 2016-2017 school year is shown in Table 5. LinkIt!©'s accuracy of prediction of the actual score band that a student scored is greater than 50% for all three assessment forms, with the lowest prediction percentage, Form A (55.3%), the middle prediction percentage, Form C (62.1%), and the highest prediction percentage, Form B (68.3%). When analyzing the data, LinkIt!© has a low percentage in over predicting the score band that a student will score on the PARCC mathematics assessment. The percentages in the higher prediction range, from least to greatest, are as follows: Form B (4.5%), Form C (6.4%), and Form A (6.8%). Given these points, LinkIt!©'s PARCC score band prediction ranges from 55.3% to 68.3%, which indicates that they are consistently accurate in their score band predictions more than 55.3% of the time.

Table 5

LinkIt!© Prediction Assessment Accuracy Rates for Predicting Actual PARCC Assessment Scores 2016-2017

	Form A Valid scores 219		Form B Valid scores 221		Form C Valid scores 219	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
2016-2017 Lower Prediction	83	37.9	60	27.1	69	31.5
2016-2017 Accurate Prediction	121	**55.3**	151	**68.3**	136	**62.1**
2016-2017 Higher Prediction	15	6.8	10	4.5	14	6.4

Note. Bold numbers represent the percentage of prediction accuracy for the tested years.

For the 2016-2017 school year, LinkIt!©'s Form B predictions were the most accurate of the three LinkIt!© mathematics assessment forms with 68.3% of students scoring in the LinkIt!© mathematics assessment predicted score band on the PARCC mathematics assessment. The data for Form B also shows that LinkIt!© underestimated their prediction of the PARCC mathematics assessment score band 27.1% of the time, where the student scored higher on the PARCC mathematics assessment, and overestimated their prediction of the PARCC mathematics score band 4.5%, where the student scored in a lower score band on the PARCC mathematics assessment. Overall, for the 2016-2017 school year, the LinkIt!© Form B score band assessment prediction were accurate most of the time (68.3%) and, when they were not accurate, the assessment score band prediction underestimated (27.1%) the score band prediction more frequently than it overestimated (4.5%) the score band prediction. Therefore, when looking at the data, it appears that LinkIt!© is cautious in their PARCC score band predictions since more students tended to do better than predicted and not worse.

Although, for the 2017-2018 school year, the LinkIt!© prediction of the PARCC mathematics assessment score band was greater than 50%, for all three LinkIt!© predictive mathematics assessment score bands for the PARCC mathematics assessment the highest percentage of accurate score band predication (2017-2018, Form B, 65.6%) was slightly lower than the 2016-2017 school year data (Form B, 68.3%). The LinkIt!© Form B mathematics assessment provided the highest predication of accuracy with 65.6% of the students scoring in the LinkIt!© mathematics assessment predicted score band for the PARCC mathematics assessment, Form A (61.9%) had the second highest accuracy percentage, and Form C (57.1%) had the lowest. As with the 2016-2017 school year, the 2017-2018 school year data indicated that the PARCC score band accuracy for the accurate prediction category is greater than 50% for all three of the LinkIt!© form assessments. The range of scores for accurate prediction score band category for the 2017-2018 school year ranged from 57.1% to 65.6%.

When analyzing the data shown in Table 6, it was noted that, with the percentage of 10.2%, the LinkIt!© Form A had the lowest prediction for overestimating the score band that the student scored on the PARCC mathematics assessment. This percentage is higher than all of the other LinkIt!© Forms of the 2016-2017 assessment predictive score band in overestimating the higher prediction score band. Overall, Form A (89.8%) had the highest percentage rates for the combined scores of lower prediction and accurate prediction on the PARCC score band predictions. Although Form A (89.8) had the highest percentage rate for the combined scores for the lower and accurate prediction, Form B (88.9%) and Form C (88.4%) were close behind.

Table 6

LinkIt!© Prediction Assessment Accuracy Rates for Predicting Actual PARCC Assessment Scores 2017-2018

	Form A Valid scores 215		Form B Valid scores 215		Form C Valid scores 217	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
2017-2018 Lower Prediction	60	27.9	50	23.3	68	31.3
2017-2018 Accurate Prediction	133	**61.9**	141	**65.6**	124	**57.1**
2017-2018 Higher Prediction	22	10.2	24	11.2	25	11.5

Note. Bold numbers represent the percentage of prediction accuracy for the tested year.

While LinkIt!© had similar accurate predication rates for both school years of the study, based on the data provided in Table 5 and Table 6, all three Forms of the LinkIt!© mathematics assessment for the 2016-2017 school year had a lower percentage of overestimating the higher predictive PARCC mathematics assessment score band: 2016-2017 Form A (6.8%), Form B (4.5%), Form C (6.4%), 2017-2018 Form A (10.2%), Form B (11.2%), Form C (11.5%). The data indicates that for both of the tested years, Form B had the highest accurate prediction percentage: 2016-2017 Form B (68.3%), 2017-2018 Form B (65.6%). Based on the data, we reject the null hypothesis and determine that there is a difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score band for students in one elementary school over a two-year period.

Figure 1 presents a snapshot of all the LinkIt!© forms over the two-year period of the research study. As indicated from the data presented, LinkIt!© has a higher percentage of predicting the PARCC mathematics assessment score band accurately than either underestimating or overestimating the score band prediction.

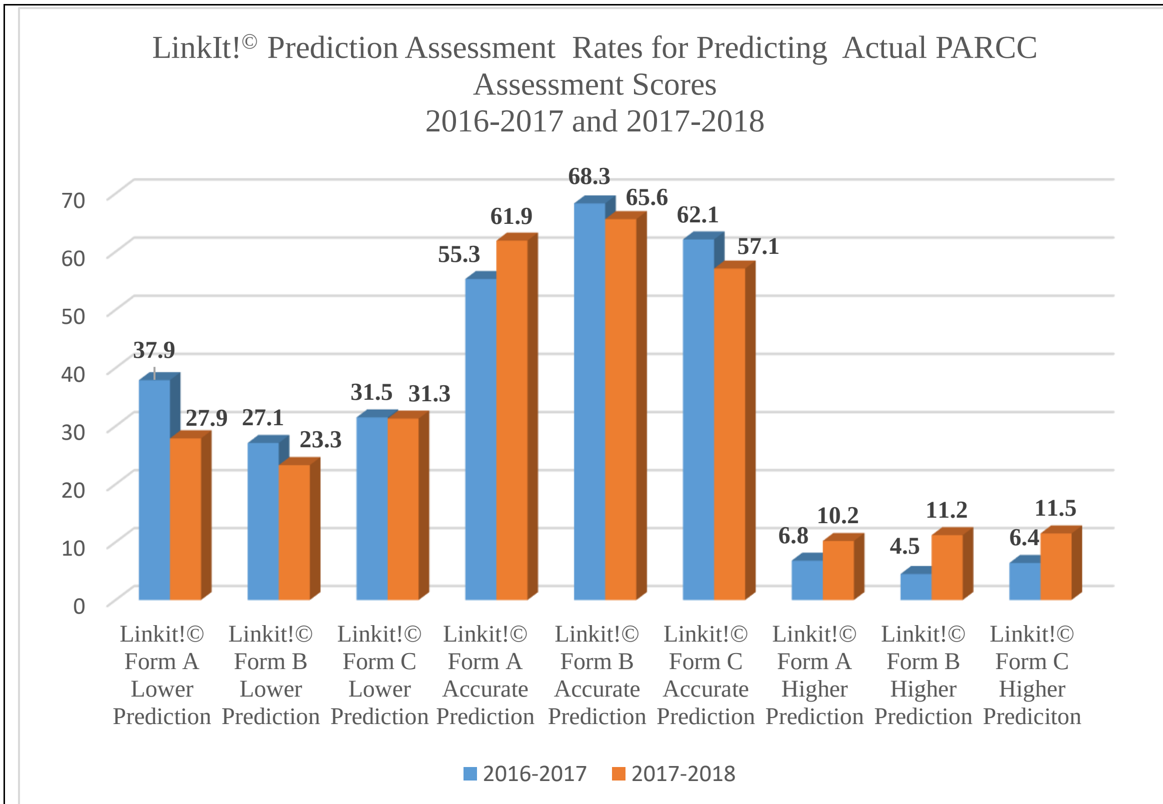

Figure 1. Prediction rates for 2016-2017 and 2017-2018

Research Question 2

When comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score, what differences in accuracy rates are revealed over the two-year period for each of the three forms, based on groupings of students in:

- general education,
- special education, and
- gifted and talented education?

In order to determine the differences in accuracy rates between each form of the LinkIt!© predictive PARCC mathematics assessment score band result and the actual PARCC mathematics assessment score band, based on groupings of students in general education, special education, and gifted and talented education, the following hypotheses were used.

Null Hypothesis: When looking at sub-groups of students, there will be no statistically significant difference in accuracy rates over the two-year period for each of the three forms based on groupings of students in general education, special education, and gifted and talented education when comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score.

Alternative Hypothesis: When looking at sub-groups of students, there will be a statistically significant difference in accuracy rates over the two-year period for each of the three forms based on groupings of students in general education, special education, and gifted and talented education when comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score.

A one-way ANOVA was used to determine if there was a statistical difference in the accuracy rates of the predictive LinkIt!© assessment score band for each form based on the following three subgroups: general education, special education, and gifted and talented education. Since this research study is looking at three subgroups, the ANOVA was used since it can compare three or more groups against each other (Knapp, 2017). Since the number of scores is different for each subgroup, an ANOVA Sidak Post Hoc was run for each of the six LinkIt!© forms. The mean difference is significant when p is less than alpha (0.05).

Table 7

ANOVA Results for the LinkIt!© 2016-2017 Form A Subgroup Comparison

2016-2017 LinkIt!© Subgroups Form A	2016-2017 Subgroups Form A	Mean Difference	Standard Error	Sig.
General Education	Special Education	.058	.105	.928
	Gifted and Talented	-.110	.101	.621
Special Education	General Education	-.058	.105	.928
	Gifted and Talented	-.168	.126	.456
Gifted and Talented	General Education	.110	.101	.621
	Special Education	.168	.126	.456

Based on information from the ANOVA Sidak Post Hoc analysis, there is evidence to suggest (see Table 7) that the 2016-2017 Link!© Form A did not differ significantly across the following subgroups: the general education, special education and gifted and talented education [F(2, 216) = .961, p=0.384]. Therefore, we accept the null hypothesis. A Sidak Post Hoc analysis revealed that no pair of comparisons was significantly different.

Table 8

ANOVA Results for the LinkIt!© 2016-2017 Form B Subgroup Comparison

2016-2017 LinkIt!© Subgroups Form B	2016-2017 Subgroups Form B	Mean Difference	Standard Error	Sig.
General Education	Special Education	-.089	.091	.693
	Gifted and Talented	.069	.088	.818
Special Education	General Education	.089	.091	.693
	Gifted and Talented	.158	.109	.381
Gifted and Talented	General Education	-.069	.088	.818
	Special Education	-.158	.109	.381

The data analysis results presented in Table 8, indicated that there is evidence to suggest that current 2016-2017 Link!© Form B did not differ significantly across the following subgroups: general education, special education, and gifted and talented education [F(2, 218) = 1.060, p=0.348]. Therefore, we accept the null hypothesis. A Sidak Post Hoc analysis revealed that no pair of comparisons was significantly different.

Table 9

ANOVA Results for the LinkIt!© 2016-2017 Form C Subgroup Comparison

2016-2017 LinkIt!© Subgroups Form C	2016-2017 Subgroups Form C	Mean Difference	Standard Error	Sig.
General Education	Special Education	-.093	.099	.725
	Gifted and Talented	.063	.096	.883
Special Education	General Education	.093	.099	.725
	Gifted and Talented	.156	.119	.469
Gifted and Talented	General Education	-.063	.096	.883
	Special Education	-.156	.119	.469

When analyzing the data from the 2016-2017 Link!© Form C (see Table 9), there is evidence to suggest that the 2016-2017 Link!© Form C did not differ significantly across the following subgroups: general education, special education, and gifted and talented education [F(2, 216) = .875, p=0.418]. Therefore, we accept the null hypothesis.

A Sidak Post Hoc analysis revealed that no pair of comparisons was significantly different.

There is evidence to suggest, when looking at the data presented in Table 10, that the 2017-2018 Link!© Form A did not differ significantly across the general education, special education, and gifted and talented education subgroups [F(2, 212) = .417, p=0.660]. Therefore, we accept the null hypothesis. A Sidak Post Hoc analysis revealed that no pair of comparisons was significantly different.

Table 10

ANOVA Results for the LinkIt!© 2017-2018 Form A Subgroup Comparison

2017-2018 LinkIt!© Subgroups Form A	2017-2018 Subgroups Form A	Mean Difference	Standard Error	Sig.
General Education	Special Education	-.068	.105	.886
	Gifted and Talented	-.080	.102	.815
Special Education	General Education	.068	.105	.886
	Gifted and Talented	-.012	.126	1.000
Gifted and Talented	General Education	.080	.102	.815
	Special Education	.012	.126	1.000

Based on the data analysis of the ANOVA information in Table 11, there is evidence to suggest that the 2017-2018 Link!© Form B differed significantly across the subgroups [F(2, 212) = .3.447, p=0.034]. P (0.034) is less than alpha (0.05); therefore, we reject the null hypothesis. A Sidak Post Hoc analysis revealed that special education students and gifted and talented students were significantly different. No other pair of comparisons were significant.

Table 11

ANOVA Results for the LinkIt!© 2017-2018 Form B Subgroup Comparison

2017-2018 LinkIt!© Subgroups Form B	2017-2018 Subgroups Form B	Mean Difference	Standard Error	Sig.
General Education	Special Education	-.214	.101	.101
	Gifted and Talented	.090	.097	.733
Special Education	General Education	.214	.101	.101
	Gifted and Talented	**.304***	.120	**.036**
Gifted and Talented	General Education	-.090	.097	.733
	Special Education	**-.304***	.120	**.036**

Note. * The mean difference is significant at the 0.05 level.
Bold indicates significant difference.

When analyzing the data presented in Table 12, there is evidence to suggest that the 2017-2018 Link!© Form C did not differ significantly across the following subgroups: general education, special education, and gifted and talented education [F(2, 214) = 2.390, p=0.094]. Therefore, we accept the null hypothesis. A Sidak Post Hoc analysis revealed that no pair of comparisons was significantly different.

Table 12

ANOVA Results for the LinkIt!© 2017-2018 Form C Subgroup Comparison

2017-2018 LinkIt!© Subgroups Form C	2017-2018 Subgroups Form C	Mean Difference	Standard Error	Sig.
General Education	Special Education	-.197	.110	.205
	Gifted and Talented	.077	.106	.848
Special Education	General Education	.197	.110	.205
	Gifted and Talented	.275	.131	.108
Gifted and Talented	General Education	-.077	.106	.848
	Special Education	-.275	.131	.108

Research Question 3

What is the relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score?

When determining if there is a relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score the following hypotheses were used:

Null Hypothesis: There will be no statistically significant relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score.

Alternative Hypothesis: There will be a statistically significant relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score.

Research Question 3 investigated the relationship, over the two year period of the research study, between two continuous variables for all three LinkIt!© forms PARCC predictive mathematics assessment score band and the actual PARCC mathematics assessment score band results to determine if there is a relationship between the two. A Pearson r correlation is the appropriate statistical test for this investigation. The following guideline will be used to determine the strength and weakness of the correlation:

- Correlation (r) values between 0 and 0.3 are considered weak
- Correlation (r) values between 0.3 but less than 0.7 are considered moderate
- Correlation (r) values greater than 0.7 are considered strong (Tokpah, (2018). EDU 8096 Dissertation Data Analysis [slide 98], retrieved from https://delval.blackboard.com/webapps/portal/execute/tabs/tabAction?tab_tab_group_id=_31_1).

Table 13

2016-2017 LinkIt!© Form A Mathematics Score Band 2016-2017 PARCC Mathematics Score Band Skewness and Kurtosis Analysis

		Value	SE	2SE	Decision
2016-2017 LinkIt!© Form A Mathematics Score Band	Skewness	-.221	.165	.330	Normal
	Kurtosis	-.184	.329	.658	Normal
2016-2017 PARCC Mathematics Score Band	Skewness	-.892	.165	.330	Normal
	Kurtosis	1.849	.329	.658	Not Normal

A Pearson r correlation was run on the data set for the 2016-2017 LinkIt!© Form A predictive mathematics assessment score band and the actual PARCC mathematics assessment score band result to determine if there is a relationship between the two. Based on the skewness statistics for the 2016-2017 LinkIt!© Form A mathematics assessment score bands and the actual 2016-2017 PARCC mathematics assessment score bands as shown in Table 13, the variables are normally distributed. Homoscedasticity is "the arrangement of points on a scatterplot wherein most of the points are in the middle of the distribution" (Knapp, 2017, p. 277). To check for homoscedasticity, a comparison of the largest variance and the smallest variance was conducted. Largest variance/smallest variance = .640/.590 = 1.08. Since the ratio does not exceed 1.5, the groups satisfy the requirement of homoscedasticity. Therefore, since the ratio of the variances is 1.08, we assume that the two variables are homoscedastic.

Table 14

2016-2017 LinkIt!© Form A Mathematics Score Band and 2016-2017 PARCC Mathematics Score Band Correlation

Correlations

		2016-2017 Form A Mathematics Score	2016-2017 PARCC Mathematics Score
2016-2017 LinkIt!© Form A Mathematics Score Band	Pearson Correlation	1	**.542****
	Sig. (2-tailed)		.0001
	N	217	217
2016-2017 PARCC Mathematics Score Band	Pearson Correlation	**.542****	1
	Sig. (2-tailed)	.0001	
	N	217	217

*Note.*** Correlation is significant at the 0.01 level (2-tailed).
Bold indicates significant correlation

The LinkIt!© Form A investigation analyzed data for 217 students during the 2016-2017 school year. The Pearson r correlation r value (r= .542, p=0.001) is higher than 0.3, which indicates that there is evidence to suggest that a significant moderate (positive) correlation between the 2016-2017 LinkIt!© Form A mathematics assessment PARCC prediction score band and the actual PARCC mathematics assessment score band for the investigation subjects (see Table 14). Since the p value for the Pearson r correlation (p=0.001) is less than alpha at (0.05) we reject the null hypothesis. Therefore, there is a statistically significant moderate (positive) correlation between the 2016-2017 LinkIt!© Form A mathematics assessment PARCC prediction score band and the actual PARCC mathematics assessment score band for the 217 elementary school students.

Nevertheless, a correlation between the two variables does not necessarily mean that there is a causal effect. In this study, there was no attempt to determine a cause/effect relationship; therefore, no conclusion can be drawn to say that the factors identified as correlational had any causal effect.

Table 15

2016-2017 LinkIt!© Form B Mathematics Score Band and 2016-2017 PARCC Mathematics Score Band Skewness and Kurtosis Analysis

		Value	SE	2SE	Decision
2016-2017 LinkIt!@ Form B Mathematics Score Band	Skewness	-.757	.164	.328	Normal
	Kurtosis	-.583	.327	.654	Normal
2016-2017 PARCC Mathematics Score Band	Skewness	-.968	.164	.328	Normal
	Kurtosis	1.988	.327	.654	Not Normal

A Pearson r correlation was run on the data set for the 2016-2017 LinkIt!© Form B predictive mathematics assessment score band and the actual PARCC mathematics assessment score band results to determine if there is a relationship between the two. Based on the skewness statistics for the 2016-2017 LinkIt!© Form B PARCC predictive mathematics assessment score bands and the actual 2016-2017 PARCC mathematics assessment score bands as shown in Table 15, the variables are normally distributed. Homoscedasticity is "the arrangement of points on a scatterplot wherein most of the points are in the middle of the distribution" (Knapp, 2017, p. 277). To check for homoscedasticity, a comparison of the largest variance and the smallest variance was conducted. Largest variance/smallest variance = .624/.583 = 1.07. Since the ratio does not exceed 1.5, the groups satisfy the requirement of homoscedasticity. Therefore, since the ratio of the variances is 1.07, we assume that the two variables are homoscedastic.

Table 16

2016-2017 LinkIt!© Form B Mathematics Score Band and 2016-2017 PARCC Mathematics Score Band Correlation

Correlations

		2016-2017 Form B Mathematics Score	2016-2017 PARCC Mathematics Score
2016-2017 LinkIt!© Form B Mathematics Score Band	Pearson Correlation	1	**.743****
	Sig. (2-tailed)		.0001
	N	219	219
2016-2017 PARCC Mathematics Score Band	Pearson Correlation	**.743****	1
	Sig. (2-tailed)	.0001	
	N	219	219

Note. ** Correlation is significant at the 0.01 level (2-tailed).
Bold indicates significant correlation

The LinkIt!© Form B investigation analyzed data for 219 elementary students during the 2016-2017 school year. The Pearson r correlation r value (r= .743, p=0.001) is higher than 0.7, which indicates that there is evidence to suggest that a significant strong (positive) correlation between the 2016-2017 LinkIt!© Form B mathematics assessment PARCC prediction score band and the PARCC mathematics assessment score band for the investigation subjects (see Table 16). Since the p value for the Pearson r correlation (p=0.001) is less than alpha at (0.05), we reject the null hypothesis. Therefore, there is a statistically significant strong (positive) correlation between the 2016-2017 LinkIt!© Form B mathematics assessment PARCC prediction score band and the actual PARCC mathematics assessment score band for the 219 elementary school students. Nevertheless, a correlation between the two variables does not necessarily mean that there is a causal effect. In this study, there was no attempt to determine a cause/effect relationship; therefore, no conclusion can be drawn to say that the factors identified as correlational had any causal effect.

Table 17

2016-2017 LinkIt!© Form C Mathematics Score Band and 2016-2017 PARCC Mathematics Score Band Skewness and Kurtosis Analysis

		Value	SE	2SE	Decision
2016-2017 LinkIt!© Form C Mathematics Score Band	Skewness	-.689	.165	.360	Normal
	Kurtosis	-.181	.329	.658	Normal
Scores2016-2017 PARCC Mathematics Score Band	Skewness	-.990	.165	.330	Normal
	Kurtosis	2.059	.329	.658	Not Normal

A Pearson r correlation was run on the data set for the 2016-2017 LinkIt!© Form C PARCC predictive mathematics score band and the actual PARCC mathematics assessment score band results. Based on the skewness statistics for 2016-2017 LinkIt!© Form C PARCC predictive mathematics assessment score bands and the actual 2016-2017 PARCC mathematics assessment score band as shown in Table 17, the variables are normally distributed. Homoscedasticity is "the arrangement of points on a scatterplot wherein most of the points are in the middle of the distribution" (Knapp, 2017, p. 277).

To check for homoscedasticity, a comparison of the largest variance and the smallest variance was conducted. Largest variance/smallest variance = .682/.620 = 1.1. Since the ratio of the largest sample variance to the smallest sample variance does not exceed 1.5, the groups satisfy the requirement of homoscedasticity. Therefore, since the ratio of the variances is 1.1, we assume that the two variables are homoscedastic.

Table 18

2016-2017 LinkIt!© Form C Mathematics Score Band and 2016-2017 PARCC Mathematics Score Band Correlation

Correlations

		2016-2017 Form C Mathematics Score	2016-2017 PARCC Mathematics Score
2016-2017 LinkIt!© Form C Mathematics Score Band	Pearson Correlation	1	**.698****
	Sig. (2-tailed)		.0001
	N	217	217
2016-2017 PARCC Mathematics Score Band	Pearson Correlation	**.698****	1
	Sig. (2-tailed)	.0001	
	N	217	217

Note. ** Correlation is significant at the 0.01 level (2-tailed).
Bold indicates significant correlation

The LinkIt!© Form C investigation analyzed data for 217 elementary students during the 2016 – 2017 school year. The Pearson r correlation r value (r= .698, p=0.001) is higher than 0.3, which indicates that there is evidence to suggest that a significant moderate (positive) correlation between the 2016-2017 LinkIt!© Form C mathematics assessment PARCC prediction score band and the PARCC mathematics assessment score band for the investigation subjects (see Table 18). Since the p value for the Pearson r correlation (p=0.001) is less than alpha at (0.05) we reject the null hypothesis. Therefore, there is a statistically significant moderate (positive) correlation between the 2016-2017 LinkIt!© Form C mathematics assessment PARCC prediction score band and the PARCC mathematics assessment score band for the 217 elementary school students. Nevertheless, a correlation between the two variables does not necessarily mean that there is a causal effect. In this study, there was no attempt to determine a cause/effect relationship; therefore, no conclusion can be drawn to say that the factors identified as correlational had any causal effect.

Table 19

2017-2018 LinkIt!© Form A Mathematics Score Band and 2017-2018 PARCC Mathematics Score Band Skewness and Kurtosis Analysis

		Value	SE	2SE	Decision
2017-2018 LinkIt!© Form A Mathematics Score Band	Skewness	-.070	.167	.334	Normal
	Kurtosis	-.430	.333	.666	Normal
2017-2018 PARCC Mathematics Score Band	Skewness	-.773	.167	.334	Normal
	Kurtosis	.912	.333	.666	Not Normal

A Pearson r correlation was run on the data set for the 2017-2018 LinkIt!© Form A PARCC predictive mathematics assessment score bands and the actual PARCC mathematics assessment score band results to determine if there is a relationship between the two. Based on the skewness statistics for the 2017-2018 LinkIt!© Form A PARCC predictive mathematics assessment score bands and the actual 2017-2018 PARCC mathematics assessment score bands as shown in Table 19, the variables are normally distributed. Homoscedasticity is "the arrangement of points on a scatterplot wherein most of the points are in the middle of the distribution" (Knapp, 2017, p. 277). To check for homoscedasticity, a comparison of the largest variance and the smallest variance was conducted. Largest variance/smallest variance = .638/.568 = 1.1. Since the ratio does not exceed 1.5, the groups satisfy the requirement of homoscedasticity. Therefore, since the ratio of the variances is 1.1, we assume that the two variables are homoscedastic.

Table 20

2017-2018 LinkIt!© Form A Mathematics Score Band and 2017-2018 PARCC Mathematics Score Band Correlation

Correlations

		2017-2018 Form A Mathematics Score	2017-2018 PARCC Mathematics Score
2017-2018 LinkIt!© Form A Mathematics Score	Pearson Correlation	1	**.628****
	Sig. (2-tailed)		.0001
	N	211	211
2017-2018 PARCC Mathematics Score	Pearson Correlation	**.628****	1
	Sig. (2-tailed)	.0001	
	N	211	211

Note. ** Correlation is significant at the 0.01 level (2-tailed).
Bold indicates significant correlation

The LinkIt!© Form A investigation analyzed data for 211 elementary students during the 2017-2018 school year. The Pearson r correlation r value (r= .628, p=0.001) is higher than 0.3, which indicates that there is evidence to suggest that a significant moderate (positive) correlation between 2017-2018 LinkIt!© Form A mathematics assessment PARCC prediction score band and the actual PARCC mathematics assessment score band for the investigation subjects (see Table 20). Since the p value for the Pearson r correlation (p=0.001) is less than alpha at (0.05) we reject the null hypothesis. Therefore, there is a statistically significant moderate (positive) correlation between the 2017-2018 LinkIt!© Form A mathematics assessment PARCC prediction score band and the actual PARCC mathematics assessment score band for the 211 elementary school students. Nevertheless, a correlation between the two variables does not necessarily mean that there is a causal effect. In this study, there was no attempt to determine a cause/effect relationship; therefore, no conclusion can be drawn to say that the factors identified as correlational had any causal effect.

Table 21

2017-2018 LinkIt!© Form B Mathematics Score Band and 2017-2018 PARCC Mathematics Score Band Skewness and Kurtosis Analysis

		Value	SE	2SE	Decision
2017-2018 LinkIt!© Form B Mathematics Score Band	Skewness	-.459	.167	.334	Normal
	Kurtosis	.313	.333	.666	Normal
2017-2018 PARCC Mathematics Score Band	Skewness	-.754	.167	.334	Normal
	Kurtosis	.865	.333	.666	Not Normal

A Pearson r correlation was run on the data set for the 2017-2018 LinkIt!© Form B PARCC predictive mathematics assessment score bands and the actual PARCC mathematics assessment score band results to determine if there is a relationship between the two. Based on the skewness statistics for the 2017-2018 LinkIt!© Form B PARCC predictive mathematics assessment score bands and the actual 2017-2018 PARCC mathematics assessment score bands as shown in Table 21, the variables are normally distributed. Homoscedasticity is "the arrangement of points on a scatterplot wherein most of the points are in the middle of the distribution" (Knapp, 2017, p. 277). To check for homoscedasticity, a comparison of the largest variance and the smallest variance was conducted. Largest variance/smallest variance = .565/.570 = 0.99. Since the ratio does not exceed 1.5, the groups satisfy the requirement of homoscedasticity. Therefore, since the ratio of the variances is 0.99, we assume that the two variables are homoscedastic.

Table 22

2017-2018 LinkIt!© Form B Mathematics Score Band and 2017-2018 PARCC Mathematics Score Band Correlation

Correlations

		2017-2018 Form B Mathematics Score	2017-2018 PARCC Mathematics Score
2017-2018 LinkIt!© Form B Mathematics Score	Pearson Correlation	1	**.634****[**]
	Sig. (2-tailed)		.0001
	N	211	211
2017-2018 PARCC Mathematics Score	Pearson Correlation	**.634****[**]	1
	Sig. (2-tailed)	.0001	
	N	211	211

Note. ** Correlation is significant at the 0.01 level (2-tailed).
Bold indicates significant correlation

The LinkIt!© Form B investigation analyzed data for 211 elementary students during the 2017-2018 school year. The Pearson r correlation r value (r= .634, p=0.001) is higher than 0.3, which indicates that there is evidence to suggest that a significant moderate (positive) correlation between 2017-2018 LinkIt!© Form B mathematics assessment PARCC prediction score band and the actual PARCC mathematics score band for the investigation subjects (see Table 22). Since the p value for the Pearson Correlation (p=0.001) is less than alpha at (0.05) we reject the null hypothesis. Therefore, there is a statistically significant moderate (positive) correlation between the 2017-2018 LinkIt!© Form B mathematics assessment PARCC prediction score band and the PARCC mathematics assessment score band for the 211 elementary school students. Nevertheless, a correlation between the two variables does not necessarily mean that there is a causal effect. In this study, there was no attempt to determine a cause/effect relationship; therefore, no conclusion can be drawn to say that the factors identified as correlational had any causal effect.

Table 23

2017-2018 LinkIt!© Form C Mathematics Score Band and 2017-2018 PARCC Mathematics Score Band Skewness and Kurtosis Analysis

		Value	SE	2SE	Decision
2017-2018 LinkIt!© Form C Mathematics Scores	Skewness	-.216	.167	.364	Normal
	Kurtosis	-.398	.332	.664	Normal
2017-2018 PARCC Mathematics Score	Skewness	-.765	.167	.364	Normal
	Kurtosis	.903	.332	.664	Not Normal

A Pearson r correlation was run on the data set for the 2017-2018 LinkIt!© Form C predictive mathematics assessment score bands and the actual PARCC mathematics assessment score band results to determine if there is a relationship between the two.

Based on the skewness statistics for the 2017-2018 LinkIt!© Form B mathematics assessment score bands and the 2017-2018 PARCC mathematics assessment score bands as shown in the Table 23, the variables are normally distributed. Homoscedasticity is "the arrangement of points on a scatterplot wherein most of the points are in the middle of the distribution" (Knapp, 2017, p. 277). To check for homoscedasticity, a comparison of the largest variance and the smallest variance was conducted. Largest variance/smallest variance = .636/.565 = 1.13. Since the ratio does not exceed 1.5, the groups satisfy the requirement of homoscedasticity. Since the ratio of the variances is 1.13, we assume that the two variables are homoscedastic.

Table 24

2017-2018 LinkIt!© Form C Mathematics Score Band and 2017-2018 PARCC Mathematics Score Band Correlation

Correlations

		2017-2018 Form C Mathematics Score	2017-2018 PARCC Mathematics Score
2017-2018 LinkIt!© Form C Mathematics Score	Pearson Correlation	1	**.626****
	Sig. (2-tailed)		.0001
	N	213	213
2017-2018 PARCC Mathematics Score	Pearson Correlation	**.626****	1
	Sig. (2-tailed)	.0001	
	N	213	213

Note. **Correlation is significant at the 0.01 level (2-tailed).
Bold indicates significant correlation

The LinkIt!© Form C investigation analyzed data for 213 elementary students during the 2017-2018 school year. The Pearson Correlation r value ($r = .626$, $p = 0.001$) is higher than 0.3, which indicates that there is evidence to suggest that a significant moderate (positive) correlation between the 2017-2018 LinkIt!© Form C mathematics assessment PARCC prediction score band and the PARCC mathematics assessment score band for the investigation subjects (see Table 24). Since the p value for the Pearson r correlation ($p = 0.001$) is less than alpha at (0.05) we reject the null hypothesis. Therefore, there is a statistically significant moderate (positive) correlation between the 2017-2018 LinkIt!© Form C mathematics assessment PARCC prediction score band and the PARCC mathematics assessment score band for the 213 elementary school students. Nevertheless, a correlation between the two variables does not necessarily mean that there is a causal effect. In this study, there was no attempt to determine a cause/effect relationship; therefore, no conclusion can be drawn to say that the factors identified as correlational had any causal effect.

Research Question 4

What is the accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period by grade level?

The following hypotheses will be used to determine the accuracy rate of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score based on grade level:

Null Hypothesis: There will be no difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period by grade level.

Alternative Hypothesis: There will be a difference in accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period by grade level.

Descriptive statistics were used to determine the frequency and percentages for the prediction of accuracy for the 2016-2017 and 2017-2018 school years for the six LinkIt!© mathematics assessment forms. Scores were categorized into three categories: lower prediction, accurate prediction, and higher prediction. A score was categorized in the lower prediction category if the LinkIt!© PARCC mathematics assessment score band prediction was lower than what the student actually scored on the PARCC mathematics assessment. A score in the accurate prediction category indicates that the LinkIt!© PARCC mathematics assessment score band prediction was equal to the student PARCC mathematics assessment score. Finally, a score in the higher prediction category indicates that the LinkIt!© PARCC mathematics assessment score band prediction was higher than what the student actually scored on the PARCC mathematics assessment.

During the 2017-2018 school year, the LinkIt!© Form B mathematics assessment in grade six was the most accurate prediction in the lower prediction percentage (see Table 25). Data from Form B indicates that there were no students (0.0%) in which LinkIt!©'s PARCC mathematics assessment score band prediction was lower than what the student actually scored on the PARCC mathematics assessment. There were five times that the LinkIt!© data indicated that greater than or equal to 50% of the students would score lower on the PARCC mathematics assessment than the students' actual PARCC assessment score: 16-17 Form A Grade 3 (61.9), Grade 6 (51.2%), 16-17 Form C Grade 8 (52.3%), 17-18 Form C Grade 7 (50.0), and Grade 8 (54.5%).

Table 25

2016-2017 and 2017- 2018 Grade Level LinkIt!© Mathematics Lower Prediction Percentages

Grade Level	16-17 Form A Lower Prediction Percentage	16-17 Form B Lower Prediction Percentage	16-17 Form C Lower Prediction Percentage	17-18 Form A Lower Prediction Percentage	17-18 Form B Lower Prediction Percentage	17-18 Form C Lower Prediction Percentage
3	61.9	33.3	23.8	29.7	13.9	22.2
4	32.3	32.3	15.6	19.2	44.4	25.9
5	44.7	**10.5**	**13.2**	**17.9**	25.0	27.6
6	51.2	31.7	29.3	33.3	**0.0**	**5.1**
7	**16.7**	18.6	41.5	34.2	27.0	50.0
8	31.8	37.8	52.3	29.5	38.6	54.5

Note. Bold number indicates the highest grade level accuracy rate.

Table 26

2016-2017 and 2017- 2018 Grade Level LinkIt!© *Mathematics Accuracy Prediction Percentages*

Grade Level	16-17 Form A Accurate Prediction Percentage	16-17 Form B Accurate Prediction Percentage	16-17 Form C Accurate Prediction Percentage	17-18 Form A Accurate Prediction Percentage	17-18 Form B Accurate Prediction Percentage	17-18 Form C Accurate Prediction Percentage
3	33.3	52.4	61.9	56.8	63.9	**69.4**
4	54.8	67.7	68.8	57.7	44.4	66.7
5	55.3	**86.8**	**81.6**	**67.9**	67.9	62.1
6	48.8	68.3	70.7	61.5	**82.1**	59.0
7	**71.4**	76.7	56.1	63.2	70.3	50.0
8	56.8	53.3	40.9	59.1	52.3	38.6

Note. Bold number indicates the highest grade level accuracy rate.

When analyzing the data by grade levels, the prediction for the fifth grade level was accurate, over the six testing sessions, fifty percent of the time: 16-17 Form B

(86.8%), 16-17 Form C (81.6%), and 17-18 Form A (67.9%) (see Table 26). The other three sessions were split across three different grade levels: 16-17 Form A grade seven (71.4%), 17-18 Form B grade six (82.1%), and 17-18 Form C grade three (69.4%). The LinkIt!© Form B assessment had the highest prediction rate across both school years testing sessions with an 86.8% for the 2016-2017 school year and an 82.1% for the 2017-2018 school year. When analyzing all of the grade levels, the accuracy prediction, over all six testing sessions, ranged from 33.3% to 86.8% accurate.

Table 27

2016-2017 and 2017- 2018 Grade Level LinkIt!© Mathematics Higher Prediction Percentages

Grade Level	16-17 Form A Higher Prediction Percentage	16-17 Form B Higher Prediction Percentage	16-17 Form C Higher Prediction Percentage	17-18 Form A Higher Prediction Percentage	17-18 Form B Higher Prediction Percentage	17-18 Form C Higher Prediction Percentage
3	4.8	14.3	14.3	10.8	22.2	8.3
4	12.9	**0.0**	15.6	23.1	11.1	7.4
5	**0.0**	2.6	5.3	14.3	7.1	10.3
6	**0.0**	**0.0**	**0.0**	5.1	17.9	35.9
7	11.9	4.7	2.4	**2.6**	**2.7**	**0.0**
8	11.4	8.9	6.8	11.4	9.1	6.8

Note. Bold number indicates the highest grade level accuracy rate.

During the 2016-2017 school year, for the higher prediction percentage, grade six was the most accurate (see Table 27). LinkIt!©'s predictions did not show any students with a higher predicted LinkIt!© mathematics assessment score band than the actual PARCC mathematics assessment score band. During the 2017-2018 school year, for the higher prediction percentage, grade seven was the most accurate when determining what score band a student may score on the PARCC mathematics assessment. For the seventh grade on the Form A (2.6%) and Form B (2.7%) assessments, LinkIt!© predicted that one student would score higher on the LinkIt!© mathematics assessment than what occurred on the actual PARCC mathematics assessment and for Form C (0.0%), LinkIt!©'s predictions did not show any students with a higher predicted LinkIt!© mathematics assessment score band than the actual PARCC mathematics assessment score band.

Additional information about the student count frequency and percentage is presented in table form in the appendix. Tables 28 to 33, in Appendix E, show the student count frequency and percentages, by the testing form, for the lower prediction and upper prediction along with the accuracy prediction student frequency and percentages. The data shows that there were thirty-one times, out of a possible thirty-six, that the lower prediction percentage was greater than the higher prediction percentage. Upon further review of the data, there were thirty-two times that the lower prediction percentage was smaller than, and two times it was equal to, the accuracy prediction percentage over the two years of the research study. Based on the data, we reject the null hypothesis and determine that there is a difference in accuracy rate for the three forms of the LinkIt!© mathematics assessment PARCC predictive score band results in predicting the actual PARCC mathematics assessment score for students in one elementary school over a two-year period by grade level.

Summary

Using formative and summative assessment data, the research study examined four questions focusing on students in grades three through eight in an elementary school in New Jersey. The data indicates that the accuracy prediction rate percentage was higher more than 50% for all six LinkIt!© mathematics assessment testing sessions, ranging from 55.3% to 68.3%. When analyzing the subgroup information for the general education, special education, and the gifted and talented students, the data suggests that there is not a significant difference in the three subgroups except during the 2017-2018 school year; in the LinkIt!© Form B mathematics assessment, there is a significant difference at the p< alpha (0.05) between the special education and the gifted and talented students (p=0.034). The data also suggests that there is a significant positive correlation between all of the LinkIt!© predictive mathematics assessment score bands and the actual PARCC assessment score band. In conclusion, when reviewing the data results, it appears that LinkIt!© does not have one grade level that is consistently accurate. However, over the two years of the research study, grade five was consistent 50% of the time.

Chapter Five: Discussion

Summary of the Study

Formative and summative assessment are a part of many classrooms at various times throughout the school year. Some of the summative assessments are considered high stakes testing since it might determine if a student qualifies for an advanced placement class, a remedial course, or possibly whether or not they can graduated from high school. With the passage of the 2001 No Child Left Behind Act (NCLB), mandated assessment was required by the federal government. As the stakes for the student and the school increase from the mandated assessments, school district look at different options to help their students score higher on the assessment.

The purpose of this quasi-experimental quantitative research study was to determine if there is a nexus between the accuracy of the predictive ability of the LinkIt!© mathematics assessment and the PARCC mathematics assessment results. Two years of data (2016-2017 and 2017-2018) were analyzed from one elementary school in New Jersey. The 2016-2017 school year was the first time that LinkIt!© started providing predictive assessment data, therefore, that is the first year used in this study.

The research study analyzed data from two types of assessments, the three LinkIt!© commercially produced formative assessment predictive mathematics assessment forms as well as the PARCC standardized summative mathematics assessment score band results. The research study focused on answering four questions. Two of the questions used descriptive statistics to analyze the data based on prediction accuracy on the total population and the third through eighth grade levels. Another question used an ANOVA test to analyze the three sub-groups of student populations (general education, special education, and gifted & talented). Finally, the Pearson r correlation was used to determine if there was a relationship between the three LinkIt!© mathematics predictive score band results and the actual PARCC mathematics assessment score results. If the student data met the specified criteria, it was used in the analyses.

Summary of the Results

Research question 1. What is the accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period?

The data was categorized into three areas: lower prediction, accurate prediction, and higher prediction. The LinkIt!© and PARCC mathematics assessment score band data were analyzed using descriptive statistics, using frequency and percentages. The data indicates that out of the six mathematics assessment forms analyzed, LinkIt!© predicted the actual PARCC score band over 50% of the time. The highest percentages for both school years in the research study were the Form B assessment results. In the 2016-2017 school year, 68.3% of the students PARCC score was in the predicted score band of the LinkIt!© Form B mathematics assessment. In the 2017-2018 school year, 65.6% of the students scored in the LinkIt!© mathematics assessment predicted PARCC score band.

In the lower prediction category, the data ranged from 23.3% to 37.9%. This means that based on the LinkIt!© mathematics assessment forms, LinkIt!© underestimated the score band that the student would score on the PARCC mathematics assessment. As with the accurate prediction results, the LinkIt!© Form B mathematics assessment data was the most accurate, for both years of the study, out of the six LinkIt!© mathematics assessments.

LinkIt!© had the lowest percentage range for the higher prediction category than any of the other two categories: lower prediction and accurate prediction. In this category, LinkIt!© predicted that a student would score higher on the PARCC mathematics assessment than they actually did. The data for this category ranged from 4.5% to 11.5%. When looking at the frequency data, the number of students scoring in the higher prediction category ranged from 10 students to 25 students.

Overall, for both the 2016-2017 and the 2017-2018 school years, the LinkIt!© Form B had the highest accurate percentage and the lowest lower prediction and higher prediction percentages out of the three LinkIt!© mathematics assessment forms given over each of the two-year period.

Research question 2. When comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score, what differences in accuracy rates are revealed over the two-year period, for each of the three forms, based on groupings of students in:

- general education,
- special education, and
- gifted and talented education?

A one way ANOVA analysis was conducted to find the mean of the three subgroups: general education, special education and gifted and talented education. A Sidak Post Hoc was run for each of the six LinkIt!© mathematics assessment forms since the number of scores was different for each subgroup. Based on the data analyzed, five of the LinkIt!© mathematics forms did not differ significantly for the three subgroups. The 2017-2018 LinkIt!© Form B mathematics assessment was the only test that showed a statistically significant difference in the results. The Sidak Post Hoc analysis revealed that the gifted and talented students and the special education students were significantly different for the Form B mathematics assessment [$F(2, 214) = 2.390$, $p=0.094$].

Research question 3. What is the relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score?

A Pearson r correlation was conducted to determine the relationship between each form of the LinkIt!© predictive mathematics assessment score bands and the actual PARCC mathematics assessment score band. Five of the LinkIt!© mathematics assessment forms, over the two-year period, produced a statistically significant moderate (positive) correlation. The last assessment, the 2016-2017 LinkIt!© Form B mathematics assessment, showed a statistically significant strong (positive) correlation. Nevertheless, a correlation between the two variables does not necessarily mean that there is a causal effect. In this study, there was no attempt to determine a cause/effect relationship; therefore, no conclusion can be drawn to say that the factors identified as correlational had any causal effect.

Research question 4. What is the accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period by grade level?

Descriptive statistics, consisting of frequency and percentages, were used to determine the rate of accuracy of the three forms of the LinkIt!© mathematics predictive assessment results in predicting actual PARCC mathematics assessment scores for students in one school over a two-year period by grade level. The results were broken down into three categories: lower prediction, accurate prediction, and higher prediction.

In the lower prediction category, the data indicates that the 2017-2018 grade six Form B and Form C mathematics assessments had the lowest prediction percentage: Form B (0.0%) and Form C (5.1%). Grade five had the next lowest prediction percentages in the 2016-2017 Form B and Form C mathematics assessments: Form B (10.5%) and Form C (13.2%). The lowest percentage prediction rate over the six testing sessions ranged from 0.0% to 16.7%.

For the accurate prediction percentage, the 2016-2017 fifth grade Form B and Form C and the 2017-2018 Form A mathematics assessments had the highest percent accuracy: 16-17 Form B (86.8%), 16-17 Form C (81.6%) and 17-18 Form A (67.9%). The highest accurate prediction for the other three assessments were not consistent on one grade level. The accuracy prediction for all of the six mathematics assessment forms were over 50% with the percentages of accurate predictions ranging from 67.9% to 86.8%.

Finally, in the higher prediction category, the 2016-2017 school year, grade six, had the lowest percentage with all three mathematics assessment forms at 0.0%. This data indicates that for these three mathematics assessment forms, LinkIt!© did not predict that a student would score higher than they actually scored on the PARCC mathematics assessment. During the 2017-2018 school year, grade seven had the lowest percentage for all three mathematics assessment forms: Form A (2.6%), Form B (2.7%) and Form C (0.0%).

Relationship to Prior Research

There is a lack of research on the predictive components of a commercially produced formative assessment in determining a possible standardized summative assessment result. This research study helped to fill this gap by determining if there is a nexus between the LinkIt!© mathematics assessment score band results in predicting the actual PARCC mathematics score band, over a two year period, in one elementary school in New Jersey.

Building on the foundation of mandated assessments, this research study looked at both formative and summative assessment tools to see if there is a nexus. Formative assessment "is used to identify the gap between the expected standard and the current level of student knowledge" (Grosas, Raju, Schuett, Chuck, & Millar, 2016, p. 1596). LinkIt!© is a commercially produced formative assessment tool that provides data on how a student is progressing in the mathematics content area. Summative assessments are usually administered to determine "how much learning has occurred" (Agboola, & Hiatt, 2017, p. 76). PARCC is a summative assessment that provides the school district information on how a student has progressed on grade level expectations.

According to Sparks (2011), predictive analytics use a variety of statistical approaches to predict the probability of an assessment score. This research study investigated the ability of a commercially produced formative assessment tool's ability to predict an outcome on a state mandated assessment. LinkIt!© uses a variety of statistical methods to formulate their cut scores for the three formative assessment forms to determine the various score band ranges.

Once a student has completed a formative or summative assessment, it is important to keep an account of the assessment results. Using a data warehouse system helps teachers and administrators analyze the results by storing them in a centralized location. LinkIt!© provides school districts a data warehouse component to help teachers have assessment information assessable so that the information can be analyze when needed. Teachers are able to analyze the information from the Data Warehouse for Data Driven Decision Making (DDDM) to help develop lessons that will help the student improve their educational knowledge. DDDM, according to Anfara and Donhost (2010), includes the following five components: "1. organizing for success, 2. building assessment literacy, 3. identifying data sources, 4. aligning data systems, and 5. altering instruction" (p. 56). Anfara and Donhost (2010) also indicate that these components do not need to be completed in any particular order. Using the mathematics assessment information from the Data Warehouse gives the teachers the ability to adjust their instruction based on the needs of the students. This study used past research to build the foundation to help determine if a formative mathematics assessment has the capability of predicting the summative mathematics assessment score band result.

Recommendations for Further Research

This research study looked at the three forms of the LinkIt!© mathematics assessment score band results in predicting the actual PARCC mathematics score band, over a two year period, in one elementary school in New Jersey. In order for this study to be replicated, the researcher would need to look at data from a school district who administered the three LinkIt!© assessment forms and who participated in the PARCC assessment. The school district being studied would also need to subscribe to the LinkIt!© Navigator reports. These reports disaggregate the testing results in many different breakouts categories. One of the breakout categories is the predictive mathematics assessment score band of how the student may score on the PARCC mathematics assessment.

This research study limited its findings to one elementary school in New Jersey. Future research is necessary to see if the results of this study are consistent in other settings. Following are some further research topics that could be investigated:

- Conduct a research study that investigates more than one school to see if the findings are similar across different schools or school districts
- Conduct a study for longer than two years to determine if predictability continues to progress in accuracy
- Conduct a study in other states, using the mandated assessment required for that state, to determine if there are similar accuracy rates across different state mandated assessments
- Conduct a study with larger sample sizes for the three subgroups: general education, special education and gifted and talented education
- Conduct a study that breaks student subgroup information into different areas such as gender or ethnicity

- Conduct a study to look at schools in rural, suburban, and urban areas in any state to determine if the results are similar
- Conduct a study comparing the LinkIt!© mathematics and LinkIt!© language arts results, in relationship with the state mandated assessment, to determine if one content area is more accurate than the other
- Conduct a study comparing the LinkIt!© mathematics assessment predictive PARCC mathematics assessment score band results with another commercially produced formative assessments ability to predict the mandated PARCC mathematics assessment score band results
- Conduct a study comparing the LinkIt!© mathematics assessment using the final two years of the LinkIt!© and PARCC correlation and compare it to the first two years of the LinkIt!© mathematics assessment and the New Jersey Student Learning Assessment – Mathematics (NJSLA-M).

Implications for Practice and the Profession

This research study helped to determine the accuracy of the LinkIt!© predictive mathematics assessment score band in predicting the actual PARCC assessment score band. Using the research results from the study, school districts will need to determine if the commercially produced formative assessment tool they are currently using in the school district is able to provide the same positive results as the results of this study. If not, the district might want to look at the LinkIt!© assessment tool to determine if it would be a better fit for the district.

Second, school districts are very cautious on where they allocate funds for the district. When budgets are tight, the district needs to make sure that the money spent on each line item is going to give them the desired results. This research study has helped the school district in the study determine that the LinkIt!© mathematics assessment tool is a strong PARCC predictive mathematics assessment tool that gives the educators in the district important information. The results affirm what the district needed to know about whether to spend the money on the LinkIt!© mathematics assessment and Navigator reports since there was a strong positive correlation between the LinkIt!© predictive mathematics assessment score band in predicting the actual PARCC mathematics assessment score band.

Third, there may be school districts who are not currently using a commercially produced assessment within their districts. This research study provides data that indicates that a predictive assessment tool can be beneficial within the school district. Through the use of the Navigator report, the LinkIt!© platform provides school districts with powerful data. The information provided by LinkIt!©, in the Navigator report, helps the school district find the students' strengths and weaknesses based on the New Jersey Student Learning Standards. After teachers analyze the data results, they are able to make informed decisions on how to use the data to drive instruction in their classrooms. The Navigator report also provides colorful tables to help clearly show the teacher how the students in their classes are progressing. It would benefit school districts to see how a predictive assessment tool might help the students in their school district progress academically.

Finally, although New Jersey and many states have since discontinued using the PARCC assessment as their state mandated assessment, the results indicate that there is a significant positive correlation between the LinkIt!© predictive mathematics assessment score band in predicting the actual PARCC mathematic assessment score band. It would behoove practitioners to determine if there are similar results with their state mandated assessment. Practitioners could also review other commercially made predictive assessments to see which one is right for their educational setting.

Conclusion

The purpose of this quasi-experimental quantitative research study was to determine if there was a nexus between the accuracy of the score band predictive ability of the LinkIt!© mathematics assessment and the PARCC mathematics assessment score band results. This research study looked at the LinkIt!© mathematics assessment and the Partnership for Assessment of Readiness for College and Career (PARCC) mathematics assessment data from a two year period, 2016-2017 and 2017-2018, in one elementary school in New Jersey.

Based on the research findings, the data suggests that the predicted LinkIt!© mathematics assessment score band has the ability to predict the score band that a student will score on the PARCC mathematics assessment over 50% of the time. As indicated from the data, LinkIt!© has a higher percentage of predicting the PARCC mathematics assessment score band accurately than either underestimating or overestimating the score band prediction. Out of the remaining percentages, LinkIt!© has underestimated more often than they have overestimated the score band results. Therefore, when looking at the data, it appears that LinkIt!© is cautious in their PARCC score band predictions since more students tended to do better than predicted and not worse.

Based on the data analysis, there is evidence to suggest that when comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score there is not a significant difference between the three subgroups (general education, special education, and gifted and talented) in the research study. The 2017-2018 LinkIt!© Form B mathematics assessment was the only test that showed a statistically significant difference in the results. The Sidak Post Hoc analysis revealed that the gifted and talented students and the special education students were significantly different for the Form B mathematics assessment [$F(2, 214) = 2.390$, $p=0.094$].

However, when analyzing the relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score, the results suggested that there is a significant positive correlation between the two mathematics assessments. Finally, when determining potential grade level differences, although grade five was the most accurate for 50% of the time over the six mathematics assessment comparisons, the highest accurate prediction for the other three assessments were not consistent on one grade level. LinkIt!© did not have one grade level that was consistently accurate for all six assessment comparisons.

The information gathered from the results of this study are important since there is evidence to suggest that there is a significant positive correlation between the LinkIt!© predictive mathematics assessment score band results and the actual PARCC mathematics assessment score band and it is worth using this information to make data-driven decision-making decisions. If the educator uses the information provided by LinkIt!© in their Navigator report, they would be able to determine the areas that instruction needs to focus on to help the students in their class progress academically.

Overall, formative assessment is an important component of the educational system by providing information on what the student still needs to master to increase their academic knowledge. Using a predictive assessment can be a valuable component of formative assessments if it helps to determine how a student might score on the state mandated assessment. Finally, the evidence of the research study suggests that the LinkIt!© mathematics assessment PARCC predictive score band results and the actual PARCC mathematics assessment score, in their Navigator report, is evidence that the predictive elements work.

References

Admin. (2017, December 1). About. Retrieved from https://parcc-assessment.org/about/

Agboola, O. O., & Hiatt, A. C. 2. (2017). Delivery of summative assessment matters for improving at-risk student learning. *Journal of College Science Teaching, 47*(1), 76-82. doi:10.2505/4/jcst17_047_01_76

AlDahdouh, A. A., Osório, A. J., & Caires, S. (2015). Understanding knowledge network, learning and connectivism. *Online Submission, 12*, 3-21. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=ED572896&authtype=sso&custid=s9004892&site=eds-live

Anfara, V. A., Jr., & Donhost, M. J. (2010). Data-driven decision making. *Middle School Journal, 42*(2), 56-63. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eue&AN=508192156&authtype=sso&custid=s9004892&site=eds-live

Blikstein, P., & Worsley, M. (2016). Multimodal learning analytics and education data mining: Using computational technologies to measure complex learning tasks. *Journal of Learning Analytics, 3*(2), 220-238. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ1126864&authtype=sso&custid=s9004892&site=eds-live

Brookhart, S. M. (2004). Classroom Assessment: Tensions and Intersections in Theory and Practice. *Teachers College Record, 106*(3), 429–458. doi: 10.1111/j.1467-9620.2004.00346.x

Brown, E. (2015, March 7). Some parents across the country are revolting against standardized testing. Retrieved from https://www.washingtonpost.com/local/education/some-parents-across-the-country-are-revolting-against-standardized-testing/2015/03/05/e2abd062-c1e1-11e4-9ec2-b418f57a4a99_story.html?utm_term=.fff2cf30b3d1

Caffrey, E., Fuchs, D., & Fuchs, L. S. (2008). The predictive validity of dynamic assessment: A review. *Journal of Special Education, 41*(4), 254-270. doi:10.1177/0022466907310366

Casalaspi, D. (2017). The making of a "Legislative miracle": The elementary and secondary education act of 1965. *History of Education Quarterly, 57*(2), 247-277. doi:10.1017/heq.2017.4

Changing the way teachers teach and students learn. (2015). *T H E Journal, 42*(1), 11. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=100567179&authtype=sso&custid=s9004892&site=eds-live

Clark, A. (2015, February 17). NJEA launches ad campaign against PARCC tests. Retrieved from https://www.nj.com/education/2015/02/njea_launches_ad_campaign_against_parcc.html

Clark, A. (2015, April 22). N.J. schools with high PARCC opt outs could have to make changes, education commissioner says. Retrieved from https://www.nj.com/education/2015/04/nj_education_commissioner_pledges_sanctions_over_p.html

Colburn, A. (2007). Constructivism and conceptual change, part I. *Science Teacher, 74*(7), 10. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eue&AN=508002006&authtype=sso&custid=s9004892&site=eds-live

Data Warehousing, Analytics, Assessment Solutions. (2018, March 2). Retrieved from http://www1.linkit.com/

Datnow, A., & Hubbard, L. (2016). Teacher capacity for and beliefs about data-driven decision making: A literature review of international research. *Journal of Educational Change*, *17*(1), 7-28. doi:10.1007/s10833-015-9264-2

Dejear Jr., M. L., Chen, Y, DuBois Baber, L., & Li, R. (2018). Perceptions of data-driven decision making on student success: A study of culture, collaboration, and advocacy among community college leaders. *Community College Enterprise*, *24*(1), 41. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=edo&AN=130650177&authtype=sso&custid=s9004892&site=eds-live

DiBello, L., & Stout, W. (2007). A practical and prescriptive approach to validity--commentary. *Measurement: Interdisciplinary Research and Perspectives, 5*(2), 138-141. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ829192&authtype=sso&custid=s9004892&site=eds-live http://www.informaworld.com/openurl?genre=article&id=doi:10.1080/15366360701487260

Dixson, D. D., & Worrell, F. C. (2016). Formative and summative assessment in the classroom. *Theory into Practice, 55*(2), 153-159. doi:10.1080/00405841.2016.1148989

Duke, B., Harper, G., & Johnston, M. (2013). Connectivism as a digital age learning theory. The International HETL Review. Special Issue 2013 (pp. 4-13).

Dunn, K., Airola, D., Lo, W., & Garrison, M. (2013). Becoming data driven: The influence of teachers' sense of efficacy on concerns related to data-driven decision making. *Journal of Experimental Education, 81*(2), 222-241. doi:10.1080/00220973.2012.699899

Erdogan, S. Z., & Timor, M. (2005). A data mining application in a student database. *Journal of Aeronautics & Space Technologies / Havacilik Ve Uzay Teknolojileri Dergisi, 2*(2), 53-57. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=a9h&AN=29406812&authtype=sso&custid=s9004892&site=eds-live

Ertmer. P.A., & Newby. T. J. (2013). Behaviorism, cognitivism, constructivism: Comparing critical features from an instructional design perspective. *Performance Improvement Quarterly*, 26(2), 43-71.

Every Student Succeeds Act (ESSA). (n.d.). Retrieved from https://www.ed.gov/essa?src=rn

Every student succeeds act: Federal elementary and secondary education policy. (2017). *Congressional Digest*, *96*(7), 4-6.

Fennell, M. (2016). What educators NEED TO KNOW about ESSA. *Educational Leadership, 73*(9), 62-65. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eue&AN=116361620&authtype=sso&custid=s9004892&site=eds-live

Feuer, M. J. (2011). Politics, economics, and testing: Some reflections. *Mid-Western Educational Researcher, 24*(1), 25-29. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ943414&authtype=sso&custid=s9004892&site=eds-live http://www.mwera.org/journal.html

Fischer, C. T. (1973). Behaviorism and behavioralism. *Psychotherapy: Theory, Research & Practice, 10*(1), 2-4. doi:10.1037/h0087536

Foroughi, A. (2015). The theory of connectivism: Can it explain and guide learning in the digital age? *Journal of Higher Education Theory & Practice, 15*(5), 11-26. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eue&AN=114543820&authtype=sso&custid=s9004892&site=eds-live

Furr, R. M. (2018). *Psychometrics: An introduction*. Thousand Oaks, CA: SAGE Publications.

Garrison, C., & Ehringhaus, M. (2007). Formative and summative assessments in the classroom. Retrieved from http://www.amle.org/Publications/WebExclusive/Assessment/tabid/1120/Default.aspx

Ghaicha, A. (2016). Theoretical framework for educational assessment: A synoptic review. *Journal of Education and Practice, 7*(24), 212-231. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ1112912&authtype=sso&custid=s9004892&site=eds-live

Grey, A. C. (2010). No child left behind in art education policy: A review of key recommendations for arts language revisions. *Arts Education Policy Review, 111*(1), 8-15. doi:10.1080/10632910903228132

Grosas, A. B., Raju, S. R., Schuett, B. S., Chuck, J., & Millar, T. J. (2016). Determining if active learning through a formative assessment process translates to better performance in summative assessment. *Studies in Higher Education, 41*(9), 1595-1611. doi:10.1080/03075079.2014.988704

Guskey, T. R., & McTighe, J. (2016). Pre-assessment: Promises and cautions. *Educational Leadership, 73*(7), 38-43. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ1096139&authtype=sso&custid=s9004892&site=eds-live

Haretos, C. (2005). The no child left behind act of 2001: Is the definition of "adequate yearly progress" adequate? *Harvard Kennedy School Review, 6,* 29-46.

Han, J., Kamber, M., & Pei, J. (2012). *Data mining: concepts and techniques*. Amsterdam: Elsevier.

Harris, E. A. (2015, March 1). As common core testing is ushered in, parents and students opt out. Retrieved from https://www.nytimes.com/2015/03/02/nyregion/as-common-core-testing-is-ushered-in-parents-and-students-opt-out.html.

Hodges, B. (2013). Assessment in the post-psychometric era: Learning to love the subjective and collective. *Medical Teacher, 35*(7), 564-568. doi:10.3109/0142159X.2013.789134

Hoover, N. R. & Abrams, L. M. (2013). Teachers' instructional use of summative student assessment data. *Applied Measurement in Education, 26*(3), 219-231.

Iwatani, E. (2018). Overview of data mining's potential benefits and limitations in education research. *Practical Assessment, Research & Evaluation, 23*(15), 1-8. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eue&AN=132622639&authtype=sso&custid=s9004892&site=eds-live

Jacob, B. (2017). The changing federal role in school accountability. *Journal of Policy Analysis & Management, 36*(2), 469-477. doi:10.1002/pam.21975

James, M. (2006) Assessment, Teaching and Theories of Learning, in J. Gardner (ed.) *Assessment and Learning*, London: Sage, pp. 47–60.

Kibble, J. D. 1. (2017). Best practices in summative assessment. *Advances in Physiology Education, 41*(1), 110-119. doi:10.1152/advan.00116.2016

Klein, A., & McNeil, M. (2010). *Administration unveils ESEA reauthorization blueprint; aims to address concerns about NCLB inflexibility, look beyond test scores* Editorial Projects in Education, Inc. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=edsgov&AN=edsgcl.222400319&authtype=sso&custid=s9004892&site=eds-live

Klein, A., & Ujifusa, A., (2019). Q&A: Answering your ESSA questions. *Education Week*, *38*(27), 20-21. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eue&AN=135731922&authtype=sso&custid=s9004892&site=eds-live

Knapp, H. (2017). *Introductory statistics using Spss*. Thousand Oaks, CA: SAGE.

Kop, R., & Hill, A. (2008). Connectivism: Learning theory of the future or vestige of the past? *International Review of Research in Open & Distance Learning*, *9*(3), 1-13. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eue&AN=508035962&authtype=sso&custid=s9004892&site=eds-live

LinkIt!. (2019). *New Jersey 2019-2020: Data warehousing, assessment solutions and analytics*. New York, NY: Author.

LinkIt!. (2018). *LinkIt! Validity and Reliability Data*

Looney, J. W. (2011), Integrating formative and summative assessment: Progress toward a seamless system, OECD Education Working Papers, No. 58, OECD Publishing. http://dx.doi.org/10.1787/5kghx3kbl734-en

Mercer, C. D., & Jordan, L. (1994). Implications of constructivism for teaching math to students with moderate to mild disabilities. *Journal of Special Education, 28*(3), 290. doi:10.1177/002246699402800305

Merenda, P. F. (2003). Measurements in the future: Beyond the 20th century. *Psychological Reports, 92*(1), 209. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=edb&AN=9406412&authtype=sso&custid=s9004892&site=eds-live

Musso, M., & Cascallar, E. (2009). New approaches for improved quality in educational assessments: Using automated predictive systems in reading and mathematics. *Problems of Education in the 21st Century, 17*, 134. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=edo&AN=47531821&authtype=sso&custid=s9004892&site=eds-live

Musso, M., & Cascallar, (2009). New approaches for improved quality in educational assessments: Using automated predictive systems in reading and mathematics. *Problems of Education in the 21st Century, 17*, 134-151. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eue&AN=47531821&authtype=sso&custid=s9004892&site=eds-live

Nagowah, L. & Nagowah, S. (2009). A reflection on the dominant learning theories: Behaviourism, cognitivism and constructivism. *International Journal of Learning, 16*(2), 279-285. doi:10.18848/1447-9494/CGP/v16i02/46136

Nelson, A. R. (2016). The elementary and secondary education act at fifty: A changing federal role in American education. *History of Education Quarterly, 56*(2), 358-361. doi:10.1111/hoeq.12186

New Jersey Department of Education. (n.d.). Historical context: Overview of New Jersey's statewide testing program. Retrieved from https://www.nj.gov/education/assessment/history.shtml

New Jersey Department of Education. (n.d.). District factor groups (DFG) for school districts. Retrieved from https://www.nj.gov/education/finance/rda/dfg.shtml

New Jersey Department of Education. (n.d.). New Jersey student learning standards. Retrieved from https://www.state.nj.us/education/genfo/faq/faq_gandt.htm

New Jersey Department of Education. (n.d.). 2015 District profiles and progress targets. Retrieved from http://www.nj.gov/education/title1/accountability/progress/15/districts.shtml

New Jersey Department of Education. (n.d.). Legal protections &responsibilities. Retrieved from https://www.nj.gov/education/specialed/form/prise

New Jersey Department of Education. (n.d.). ESEA waiver accountability. Retrieved from https://www.nj.gov/education/title1/accountability/progress/15

New Jersey School Board Association. (n.d.). Your local school board, your students and PARCC: frequently asked questions. Retrieved from https://www.njsba.org/wp-content/uploads/2016/02/parcc-faq16.pdf

Nichols, P. D., Meyers, J. L., & Burling, K. S. (2009). A framework for evaluating and planning assessments intended to improve student achievement. *Educational Measurement: Issues & Practice, 28*(3), 14-23. doi:10.1111/j.1745-3992.2009.00150.x

O'Neal, C. (2012). *Data-driven decision making: A handbook for school leaders*. Eugene, OR: International Society for Technology in Education ISTE]. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=nlebk&AN=476119&authtype=sso&custid=s9004892&site=eds-live

Paré, R., & Elovitz, L. H. (2005). Data warehousing: An aid to decision-making. *T H E Journal, 32*(9), 32-33. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=a9h&AN=16893691&authtype=sso&custid=s9004892&site=eds-live

Pearson. (2018). Test administrators manual. Retrieved from https://www.nj.gov/education/archive/assessment/Spring18Grade3HSCBTTAM.pdf

Pearson. (2018). *PARCC 2017 Technical Report.* Retrieved from https://parcc-assessment.org/wp-content/uploads/2018/03/PARCC-2017-Technical-Report-Final-03162018.pdf

Pattalitan, A. P., Jr, (2016). The Implications of Learning Theories to Assessment and Instructional Scaffolding Techniques. *American Journal of Educational Research*, vol. 4, no. 9: 695-700. doi: 10.12691/education-4-9-9.

Piro, J. S., Dunlap, K., & Shutt, T. (2014). A collaborative data chat: Teaching summative assessment data use in pre-service teacher education. *Cogent Education, 1*(1), 1-24. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ1087910&authtype=sso&custid=s9004892&site=eds-live http://dx.doi.org/10.1080/2331186X.2014.968409

Robelen, E. W. (2019, February 22). 40 years after ESEA, federal role in schools is broader than ever. Retrieved from https://www.edweek.org/ew/articles/2005/04/13/31esea.h24.html

Rogers, J. L., Howard, K. I., & Vessey, J. T. (1993). Using significance tests to evaluate equivalence between two experimental groups. *Psychological Bulletin, 113*(3), 553-565. doi:10.1037/0033-2909.113.3.553

Rosenkoetter, U., & Tate, R. L. (2018). Assessing features of psychometric assessment instruments: A comparison of the COSMIN checklist with other critical appraisal tools. *Brain Impairment, 19*(1), 103-118. doi:10.1017/BrImp.2017.29

Russo, C. J., & Osborne, A. G. (2009). *Section 504 and the ADA*. Thousand Oaks, California: Corwin. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=nlebk&AN=321291&authtype=sso&custid=s9004892&site=eds-live

Santrock, J. W. (2011). *Educational psychology*. New York: McGraw-Hill Education.

Schcolnik, M., Kol, S., & Abarbanel, J. (2016). Constructivism in theory and in practice. *English Teaching Forum, 44*(4), 12-20. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ1107896&authtype=sso&custid=s9004892&site=eds-live

Sharp, L. A. (2016). ESEA reauthorization: An overview of the Every Student Succeeds Act. *Texas Journal of Literacy Education*, 4, 9–13.

Shaul, M. S., & Ganson, H. C. (2005). The no child left behind act of 2001: The federal government's role in strengthening accountability for student performance. *Review of Research in Education, 29*, 151. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=edsjsr&AN=edsjsr.3568123&authtype=sso&custid=s9004892&site=eds-live

Siemens, G. (2004). Connectivism: A learning theory for the digital age. elearnspace. http://www.elearnspace.org/Articles/connectivism.htm

Skinner, R. R., & Kuenzi, J. J. (2015). Reauthorization of the Elementary and Secondary Education Act: Highlights of the Every Student Succeeds Act. Washington, DC: Congressional Research Service.

Soland, J. (2014). Is "moneyball" the next big thing in education? *The Phi Delta Kappan,* (4), 64. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=edsjsr&AN=edsjsr.24376543&authtype=sso&custid=s9004892&site=eds-live

Sparks, S. D. (2011a). *Data mining gets traction in education; researchers sift 'data exhaust' for clues to improve learning.* Editorial Projects in Education, Inc. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=edsgov&AN=edsgcl.247343481&authtype=sso&custid=s9004892&site=eds-live

Sparks, S. D. (2011b). *Predictive data tools find uses in schools*. Editorial Projects in Education, Inc. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=edsgov&AN=edsgcl.262381065&authtype=sso&custid=s9004892&site=eds-live

Strauss, V. (2019, April 25). Teen: The PARCC Common Core test is 'the most stressful thing I've done in school'. Retrieved from https://www.washingtonpost.com/news/answer-sheet/wp/2015/01/15/teen-the-parcc-common-core-test-is-the-most-stressful-thing-ive-done-in-school/?utm_term=.cd7c9a3b8985

Taras, M. (2005). Assessment: Summative and formative: Some theoretical reflections. *British Journal of Educational Studies*, (4), 466.

Thomas, J. E. (2017). *Developmental psychology* Great Neck Publishing. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=ers&AN=89164162&authtype=sso&custid=s9004892&site=eds-live

Tokpah, C. (2018). EDU 8096 Dissertation Data Analysis [slide 98], Retrieved from https://delval.blackboard.com/webapps/portal/execute/tabs/tabAction?tab_tab_group_id=_31_1

UnderstandTheScore.org. (n.d.). Score report guide. Retrieved from http://understandthescore.org/

UnderstandTheScore.org. (n.d.). PARCC report. Retrieved from http://www.understandthescore.org/wp-content/uploads/2017/08/New-Jersey.compressed.pdf

Wilhelm, A. G., Gillespie Rouse, A., & Jones, F. (2018). Exploring differences in measurement and reporting of classroom observation inter-rater reliability. *Practical Assessment, Research & Evaluation, 23*(4) Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ1175504&authtype=sso&custid=s9004892&site=eds-live http://pareonline.net/getvn.asp?v=23&n=4

Yilmaz, K. (2011). The cognitive perspective on learning: Its theoretical underpinnings and implications for classroom practices. *Clearing House, 84*(5), 204-212. doi:10.1080/00098655.2011.568989

Young, V. M., (2018). Assessing the Cornerstone of U.S. Education Reform. *Educational Foundations*, *31*(3/4), 74-99

Zhou1, L. (2007). Supporting humanistic learning experiences through learning with technology. *International Journal of Learning, 13*(11), 131-136. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eue&AN=24953907&authtype=sso&custid=s9004892&site=eds-live

Appendix A

IRB Approval

DELAWARE VALLEY UNIVERSITY 1896

Jacqueline Royer
[redacted]

21 August 2019

RE: IRB Protocol Proposal #19004

Dear Jacqueline,

The Delaware Valley University Institutional Review Board convened on 20 August 2019 and reviewed your proposed study: "Finding the Nexus Between a Predictive Mathematics Assessment and a National Standardized Mathematics Assessment in an Elementary School." After careful review of your proposal, the committee voted to **approve** your proposal. You may begin collecting data at this time.

Your study is approved to run through 21 August 2020. If you wish to continue this study beyond that date, please submit a **Continuation Form** no later than 1 month before the expiration to ensure there is no interruption to your data collection.

Should any ethical issues arise as you carry out your study, or if you receive complaints from participants, please submit an **Incident Report Form** that describes the issue and how you will address it moving forward. This may require you to get updates approved by the IRB.

When you study is completed, please submit a **Study Completion Form**.

I wish you the best of luck with your project!

Sincerely,

Matthew S. Mutchler, Ph.D., LMFT
Chair, Delaware Valley University Institutional Review Board
irb@delval.edu

Appendix B

Letter of Interest

[Name of Superintendent]
[Name of School District]

September 11, 2018

Dear [Name of Superintendent],

I am currently a doctoral student at Delaware Valley University, located in Doylestown PA. As part of the doctoral program I will be required to conduct a research study. I would like to invite your school district to participate in this research study. The proposed study would look at information gathered from the 2016-2018 PARCC results as well as the data results from the LinkIt! Form B and Form C for the same two year school period. Using this school district information would help to answer some of the following potential research question:

1. How accurate are LinkIt! predictions of actual PARCC scores?

    a) How accurate is LinkIt! predictive assessment on PARCC assessment results based on the Form B LinkIt! assessment results?

    b) How accurate is LinkIt! predictive assessment on PARCC assessment results based on the Form C LinkIt! assessment results?

    c) Following a cohort of students in grades 3-7 during the 2016-2017 school year and students in grades 4-8 during the 2017-2018 what is the LinkIt! prediction accuracy rate for each grade level cohort of students based on the actual PARCC results?

2. How accurate are LinkIt! predictions of actual PARCC scores for three subgroups?

a) General education Form B?

b) General education Form C?

c) Special Education (includes IEP, Speech only IEP and 504) Form B?

d) Special Education (includes IEP, Speech only IEP and 504) Form C?

e) Gifted and Talented Students Form B?

f) Gifted and Talented Students Form C?

3. How accurate are LinkIt! predictions of actual PARCC scores on Form B and C by gender?

4. What is the correlation between the LinkIt! Form B and Form C predicted PARCC Mathematics assessment scores and the actual PARCC assessment score?

5. To what extent, if at all, does the grade level determine the predictability?

Below are the data fields that I would like to use for this research study for both the 2016-2017 and 2017-2018 school years:

1. Student Identifier ex: 16182301 (this is a made up number for the purpose of this study)
2. Grade level a number from 3-8
3. Gender M or F
4. General Education Yes or No
5. Special Education Yes or No
6. Gifted and Talented Yes or No
7. LinkIt! Form B Percentage
8. LinkIt! Form B Prediction (where LinkIt! predicts a student will score on the PARCC assessment)
9. LinkIt Form C Percentage
10. LinkIt! Form C Prediction (where LinkIt! predicts a student will score on the PARCC assessment)
11. PARCC Score

At no point during the collection of the data will any reference be made to the school district or identifying any student information other than the data sets listed above. If at any point a question would need to be added to the study, I will inform the school district of the change.

I believe that the data collected by answering these potential research questions will help the [Name of School District] drive instruction for all of the students who complete the LinkIt! and PARCC assessments.

Thank you for your consideration in this matter,

Jacqueline Royer
Doctoral Student
Delaware Valley University
Doylestown, PA

Appendix C

District Approval to Conduct Research

October 29, 2018

Mrs. Jacqueline Royer
[redacted]

Dear Mrs. Royer:

The [redacted] School District is willing to participate in your research study involving the LinkIt! and PARCC mathematics assessment data for the 2016-2017 and 2017-2018 school years, as part of your doctoral research through Delaware Valley University. It is the district's understanding that no identifying personal information will be used in the writing of the dissertation.

If you have any further questions regarding this information, please feel free to contact me.

Regards,

[redacted]
Superintendent

Appendix D

Revised Research Questions to District

[Name of Superintendent]
[Name of School District]

August 22, 2019

Dear [Name of Superintendent],

On August 21, 2019, the Delaware Valley University Institutional Review Board (IRB) approved the following four questions for the purpose of the requested research study:

1. What is the accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period?
2. When comparing the LinkIt!© mathematics predictive assessment results and the actual PARCC mathematics assessment score, what differences in accuracy rates are revealed over the two-year period, for each of the three forms, based on groupings of students in:
    - general education,
    - special education, and
    - gifted and talented education?
3. What is the relationship between each form of the LinkIt!© predictive mathematics assessment result and the actual PARCC mathematics assessment score?
4. What is the accuracy rate for the three forms of the LinkIt!© mathematics predictive assessment results in predicting the actual PARCC mathematics assessment score for students in one school over a two-year period by grade level?

Below are the data fields that would be required, for each student, for both the 2016-2017 and 2017-2018 school years, for the third through eighth grade students:

1. Grade Level: coded for each grade level (grades 3-8)
2. Sub Group Information
   - General Education: 1
   - Special Education: 2
   - Gifted and Talented: 3
3. LinkIt! Score Band Information - The score bands for the 2016-2017 and 2017- 2018 school years for each of the LinkIt! mathematics assessment forms (Form A, Form B and Form C).
   - Not Meeting
   - Partially Meeting
   - Approaching
   - Bubble
   - Meeting
   - Exceeding
   - NA - If a student did not take the assessment
4. PARCC Score Band Information - The score bands for the 2016-2017 and 2017- 2018 school years for each of the PARCC mathematics assessment results.
   - Did Not Yet Meet Expectations
   - Partially Met Expectations
   - Approached Expectations
   - Met Expectations
   - Exceeded Expectations
   - NA - If a student did not take the assessment

At no point during the analysis and reporting of the data will any reference be made to the school district or identifying any student information other than the data sets listed above.

Thank you for the districts participation in this research study,

Jacqueline Royer
Doctoral Student
Delaware Valley University
Doylestown, PA

Appendix E

Research Question 4 Tables

Table 28

2016-2017 LinkIt!© *Mathematics Form A*

Grade Level	Lower Prediction Frequency Student Count	Lower Prediction Percentage	Accurate Prediction Frequency Student Count	Accurate Prediction Percentage	Higher Prediction Frequency Student Count	Higher Prediction Percentage
3	13	61.9	7	33.3	1	4.8
4	10	32.3	17	54.8	4	12.9
5	17	44.7	21	55.3	0	0.0
6	21	51.2	20	48.8	0	0.0
7	7	16.7	30	**71.4**	5	11.9
8	14	31.8	25	56.8	5	11.4

Note. Bold number indicates the highest grade level accuracy rate.

Table 29

2016-2017 LinkIt!© *Mathematics Form B*

Grade Level	Lower Prediction Frequency Student Count	Lower Prediction Percentage	Accurate Prediction Frequency Student Count	Accurate Prediction Percentage	Higher Prediction Frequency Student Count	Higher Prediction Percentage
3	7	33.3	11	52.4	3	14.3
4	10	32.3	21	67.7	0	0.0
5	4	10.5	33	**86.8**	1	2.6
6	13	31.7	28	68.3	0	0.0
7	8	18.6	33	76.7	2	4.7
8	17	37.8	24	53.3	4	8.9

Note. Bold number indicates the highest grade level accuracy rate.

Table 30

2016-2017 LinkIt!© *Mathematics Form C*

Grade Level	Lower Prediction Frequency Student Count	Lower Prediction Percentage	Accurate Prediction Frequency Student Count	Accurate Prediction Percentage	Higher Prediction Frequency Student Count	Higher Prediction Percentage
3	5	23.8	13	61.9	3	14.3
4	5	15.6	22	68.8	5	15.6
5	5	13.2	31	**81.6**	2	5.3
6	12	29.3	29	70.7	0	0.0
7	17	41.5	23	56.1	1	2.4
8	23	52.3	18	40.9	3	6.8

Note. Bold number indicates the highest grade level accuracy rate.

Table 31

2017-2018 LinkIt!© *Mathematics Form A*

Grade Level	Lower Prediction Frequency Student Count	Lower Prediction Percentage	Accurate Prediction Frequency Student Count	Accurate Prediction Percentage	Higher Prediction Frequency Student Count	Higher Prediction Percentage
3	11	29.7	21	56.8	4	10.8
4	5	19.2	15	57.7	6	23.1
5	5	17.9	19	**67.9**	4	14.3
6	13	33.3	24	61.5	2	5.1
7	13	34.2	24	63.2	1	2.6
8	13	29.5	26	59.1	5	11.4

Note. Bold number indicates the highest grade level accuracy rate.

Table 32

2017-2018 LinkIt!©Mathematics Form B

Grade Level	Lower Prediction Frequency Student Count	Lower Prediction Percentage	Accurate Prediction Frequency Student Count	Accurate Prediction Percentage	Higher Prediction Frequency Student Count	Higher Prediction Percentage
3	5	13.9	23	63.9	8	22.2
4	12	44.4	12	44.4	3	11.1
5	7	25.0	19	67.9	2	7.1
6	0	0.0	32	**82.1**	7	17.9
7	10	27.0	26	70.3	1	2.7
8	17	38.6	23	52.3	4	9.1

Note. Bold number indicates the highest grade level accuracy rate.

Table 33

2017-2018 LinkIt!© *Mathematics Form C*

Grade Level	Lower Prediction Frequency Student Count	Lower Prediction Percentage	Accurate Prediction Frequency Student Count	Accurate Prediction Percentage	Higher Prediction Frequency Student Count	Higher Prediction Percentage
3	8	22.2	25	**69.4**	3	8.3
4	7	25.9	18	66.7	2	7.4
5	8	27.6	18	62.1	3	10.3
6	2	5.1	23	59.0	14	35.9
7	19	50.0	19	50.0	0	0.0
8	24	54.5	17	38.6	3	6.8

Note. Bold number indicates the highest grade level accuracy rate.