The Exploration of Data Collection and Analyzation by English Language Development Educators In New Hampshire

by

Elizabeth L. Leone, M.Ed.

A Dissertation Presented in Partial Fulfillment

of the Requirements for the Degree

Doctor of Education in Educational Leadership

Southern New Hampshire University

The Exploration of Data Collection and Analyzation by English Language Development Educators In New Hampshire

Elizabeth Leone

Submitted in Partial Fulfillment of the Requirements for the

Degree of

Doctor of Education in Educational Leadership

Graduate Education Programs
Southern New Hampshire University

DocuSigned by:
[redacted]
4E94A7546458440...

Dr. Irving Richardson- Committee Chair

DocuSigned by:
[redacted]
2A793E97D81F4B5...

Dr. Randall Case - Committee Member

DocuSigned by:
[redacted]
7B1053F96081403...

Dr. Eboni Caridine - Committee Member

ABSTRACT

Data collection and analyzation practices for English language development services are scarcely found in research, but needed in the subgroup of minority students commonly known as English language learners (Wiseman & Bell, 2021). Wiseman and Bell (2021) identified ELLs as one of the most under-documented student subgroups in the American educational system. This quantitative correlational survey study explored the importance of data collection and analyzation practices for New Hampshire ELD educators through the lens of Mandinach et al.'s (2006) data-driven decision-making (DDDM) framework. DDDM is the process of identifying data, collecting it to be analyzed and interpreted, and using it to set goals to improve educational experiences (Mandinach & Schildkamp, 2021a). The present study explored the outcome of the dependent variable of teacher self-reported data collection and analyzation, and teacher-perceived importance of data through a cross-sectional survey and correlational analysis, using the length of teaching experience as the independent variable in the measurement of covariation. Based on the findings, ELD data standards may be evaluated and better informed by the current data collection and analyzation practices in New Hampshire public school districts. With meaningful data and intentional analysis, the DDDM framework and research suggest that instructional quality will likely increase to positively impact student achievement (Dodman et al., 2021), offering exponential benefit to a subgroup of struggling ELLs (Garver, 2022).

Keywords: English language development, ESSA, Title III, data efficacy, Data Wise, data-driven decision making (DDDM), data analysis, data collection, data reporting, ELD data, equity, data warehousing, WIDA, professional learning

ACKNOWLEDGEMENTS

Many deserve acknowledgement and gratitude for their support on the journey to this achievement. To my children, Charlotte, Eloise, and Silas, you are my soul, my strength, and my best cheerleaders. I hope that watching mom's academic journey has demonstrated the perseverance necessary to make your dreams come true. You have been so patient with the endless typing and piles of research literature. When you are ready to spread your wings, I will be your biggest strength and support as you shoot for the stars.

Jeremy, thank you for being in my corner, for the emotional support, snack runs, and all your efforts to keep our life afloat while I finished strong. To my family, thank you for believing in me.

My doctoral cohort, you know better than anyone the highs and lows of this journey. We set out to change the world, and we finish strong. You all inspire me. To the many influential professors in the doctoral program, this experience has been life-changing.

To Dr. Irving Richardson, the one who caught my vision before anyone else. You believed in me and your thought-provoking questions and encouraging input helped me to believe in myself. Thank you for advocating for me as my committee chair and guiding me through my dissertation process. Dr. Eboni Caridine, you have been a role model for women in educational leadership. Despite the political nature, you have inspired me to keep fighting for what is right. Dr. Randall Case, it has been an honor to have your guidance and challenging questions.

DEDICATION

To my children, Charlotte, Eloise, and Silas, for the joy you bring to my life and your patience with my dissertation journey.

To my partner, Jeremy, for supporting the relentless pursuit of my passions and education.

To my family for inspiring me.

I love you all and would not be who I am today without you.

TABLE OF CONTENT

TITLE PAGE …………………………………………………………………… i

COMMITTEE VERIFICATION ……………………………………………… ii

COPYRIGHT ……………………………………………………………… iii

ABSTRACT ………………………………………………………………… iv

ACKNOWLEDGMENTS …………………………………………………… v

DEDICATION ………………………………………………………………vi

TABLE OF CONTENTS …………………………………………………… vii

LIST OF TABLES ………………………………………………………… ix

LIST OF FIGURES ………………………………………………………… xi

LIST OF ABBREVIATIONS ……………………………………………… xii

SECTION ONE: INTRODUCTION ………………………………………… 1

Statement of Inquiry …………………………………………………… 2

Research Question and Hypothesis …………………………………… 3

Research Methodology ………………………………………………… 4

Setting …………………………………………………………………… 5

Population & Sample …………………………………………………… 6

Research Instruments, Variables, and Procedures ……………………… 8

Instrumentation ………………………………………………………… 8

Survey …………………………………………………………………… 10

Data Collection Procedures ……………………………………………… 13

Data Analysis Procedures ………………………………………………… 14

Anticipated Ethical Issues…………………………………………………16

Assumptions …………..………………………………………..……….……. 16

Limitations and Delimitations ……………………………….…………… 17

Significance & Summary of the Inquiry ………………………..……………. 20

Key Terms………………………………………………………………… 20

Contributions to Scholarship and Practice …..……………………………..…… 23

SECTION TWO: ORGANIZATION ……………………………………………….. 26

Organizational Background ………………………..…………..…..……... 25

ESSA ………………………………………………………...………. 27

Title III ……………………………………….……………...……. 29

Organizational Analysis ……………………………..………………..…... 30

Structural Frame …………………………….………....…………….. 30

Political Frame ……………………………………………...………….. 32

Leadership Analysis …………………………………………..…………... 34

Implications of Research in the Practitioner Setting …………………………… 37

Conclusion ...………………………………………………………………… 39

SECTION THREE: LITERATURE REVIEW……………………...………………..... 41

Federal Provisions for ELD Programs……...……………………..…..……… 42

ESSA ……………………………………………………………….…... 42

WIDA Consortium …………………………………………….... 46

Current Data Practices in ELD ……………………..……………….…. 47

Theoretical Framework ……………………...…………….…………..……….. 50

Data-driven Decision Making ……………….………………..………..……. 50

Data-driven Decision-Making Framework ………………..…..…..……… 54

Data ………………………..……………………..……………………..…..... 56

Data Collection ……………………..………………...………58

Data and Information …………..…………..……………………… 65

Data and Knowledge …………………...……..…….….….…… 69

Conclusion ………………………….……………………..………...………. 71

SECTION FOUR: CONTRIBUTION TO RESEARCH ………………..…...…...……. 73

Overview of Sampling Demographics …………………...…….……...……. 74

Results of the Research Study ………………..……..……….……………..…… 76

Question One: What types of data do ELD educators report collecting and analyzing to modify instruction for English language learners? ……..... 76

Question Two: What relationship exists between the number of years an educator has taught in an ELD program and how the educator reports collecting and analyzing data to modify instruction? ………………...…...……...……. 81

Question Three: What relationship exists between the number of years an educator has taught in an ELD program and the way in which the educator reports on the importance of collecting and analyzing data to modify instruction? ………... 86

Expansion Questions ……………...………………..………………....…….. 90

Conclusion of Statistical Significance …………….…………………………….. 103

Limitations ………………..………………………….…...……………….. 106

SECTION FIVE: IMPLICATIONS AND CONTRIBUTION TO SCHOLARSHIP AND PRACTICE ..……………………………………………………………...……... 109

Summary …………..……………………...………………………….….. 109

Discussion …………..……………………..……..…………………………...…….. 110

Conclusion One: Data Analysis Decline ………...……………...……. 110

WIDA …………………….……..……………...…..………….. 112

Data Intersections …………..……………..……...……………….. 114

Conclusion Two: Lack of Data Uniformity ……………………..…….. 115

Conclusion Three: The Influence of ESSA Regulations …..…...…….. 119

Conclusion Four: More Professional Learning (PL) on DDDM ……... 122

Scholar Contribution …………..………………….… …...………..…...…….. 124

Target Journal and Rationale …………..………………….…….……. 125

Practitioner Contribution …………..………………...……………..…...…….. 126

DOKed Data Collection & Reporting ………….…………….....…….. 126

Plan for Dissemination …………..………………...………….……......…….. 129

SECTION SIX: RESEARCHER REFLECTION …………...……..………….....……. 131

Practitioner Reflection ……………….…………………….…..……..…...……. 131

Educational Leader Reflection ………………………..…..………..…...…. 133

Scholar Reflection ……………………………….………………...………...……. 135

Implications for the Future ..…………….……………………………..…...…. 138

Conclusion .……...…………………….……………….…..……….…..……. 140

REFERENCES …………………….…………………….……….....…………..…. 143

APPENDICES ...……………………..……………...……………………...……….. 162

Appendix A: Modified Survey ...……………………...…………………….. 163

Appendix B: Permission to Modify Survey ...…...……………….……..…….. 179

Appendix C: Sample Consent Letter to School Districts ...……………...…….. 180

Appendix D: Sample Endorsement Letter for District Use ...…...……....……. 182

Appendix E: Title III Program Assurances ……….……………………..……. 183

Appendix F: Open-ended Responses for Data Collection and Analyzation ….. 184

Appendix G: Open-ended Responses for Professional Learning Experiences .. 189

Appendix H: DOKed Professional Learning Experience Outline .……...……. 193

LIST OF TABLES

1: Total and ELD Enrollment in Public School Districts for 2021-2022 School Year 6

2: Rowen's Classroom Data Measurement Tools…………………………………….. 61

3: Overall Participant Demographics …………………………………….. 75

4: Descriptive Statistics for ELD Teaching Experience …………………………... 76

5: Frequency Distribution for Data Collection…………………………………….. 78

6.1: Outcome Data Usage…………………………………….. 79

6.2: Instructional Process Data Usage…………………………………….. 79

6.3: Perceptual Data Usage…………………………………….. 80

7: Frequency Distribution for Data Analysis…………………………………….. 81

8.1: Point Biserial Correlation Coefficient Analysis for Data Collection Types and Teacher Tenure …………………………………….. 82

8.2: Point Biserial Correlation Coefficient Analysis for Data Collection Types Continued …………………………………….. 83

9.1: Point Biserial Correlation Coefficient Analysis for Data Analyzation Types and Teacher Tenure …………………………………….. 84

9.2: Point Biserial Correlation Coefficient Analysis for Data Analyzation Types Continued …………………………………….. 85

10.1: Correlation of Data Collection Importance Score and Demographic …………... 87

10.2: Correlation of Data Analysis Importance Score and Demographic ..……………… 88

11.1: Importance Response Point Biserial Correlation Coefficient for Data Collection Types ……………………………………… 89

11.2: Importance Response Point Biserial Correlation Coefficient for Data Analysis

Continued ………………………………………...……………........……….. 90

12: Descriptive Statistics of PL Experiences ………...…………..………........……...... 98

13.1: Point Biserial Correlation Between Data Collection Types and PL Score ..……. 100

13.2: Point Biserial Correlation Between Data Analyzation Types and PL Score……. 100

LIST OF FIGURES

1: Organizational Map of USED …….………………………….……...…..……..….. 27

2: School District Leadership Structure …….……..…………….…………......……….. 30

3: Data-driven Decision-Making Framework ………………………….…………..…... 54

4: Teacher Tenure and Perceived Importance of Student Perceptual Data …..…......…. 89

5.1: Qualitative Data Collection Techniques Word Cloud ..……………….….......…… 92

5.2: Qualitative Data Collection Techniques Bar Graph ..……………….……......…… 92

6.1: Qualitative Data Analysis Techniques Word Cloud ..……………….………..…… 93

6.2: Qualitative Data Analysis Techniques Bar Graph ..………………….…….....…… 94

7.1: Qualitative Data Importance Word Cloud ..………………….……………......…… 95

7.2: Qualitative Data Importance Bar Graph ...……………..……………….........….. 96

8: PL Experience Frequency ...……………………………….......………....…….. 98

9: Frequency Participants Experienced Data Collection and Analyzation PL …...…..... 99

10.1: Qualitative PL Experiences Word Cloud……………….…………….........…… 101

10.2: Qualitative PL Experiences Bar Graph………………..……………….…....…… 102

11: Contradiction Frequency……………….……………………………..……...…… 108

12: Except from the ACCESS for ELLs Interpretive Guide for Score Reports ....… 113

13: DOKed DOKit! Form ……………………………..…………...…...…… 128

LIST OF ABBREVIATIONS

AMAOs	Annual measurable achievement objectives
AYP	Adequate Yearly Progress
DDDM	Data-driven decision-making
ELD	English language development
ELL(s)	English language learner(s)
ELP	English language proficiency
ESSA	The Every Student Succeeds Act
LEA	Local education agencies
MTSS	Multiple tier system support
NCLB	The No Child Left Behind act
NHED	New Hampshire Department of Education
OELA	Office of English Language Acquisition
OTL	Opportunities to learn
PL	Professional learning
SEA	State educational agency
TESOL	Teaching English to Speakers of Other Languages
USED	United States Department of Education
WIDA	World-Class Instructional Design and Assessment

SECTION ONE

INTRODUCTION TO DISSERTATION

Current research identifies the educational subgroup of English language learners (ELLs) as one of the most educationally underserved populations of students in the American educational system today (Fowler & Brown, 2018; Wiseman & Bell, 2021). With the population of ELLs rising (NCES, 2018; Jimenez, 2022; Mitchell, 2021), quality, data-inspired decisions for educating these students are needed more than ever before (Wiseman & Bell, 2021). The Every Student Succeeds Act (ESSA) and the subsequent, Title III program, attempt to increase English language proficiency for the ELL subgroup; however, this federally mandated program has struggled to provide educational data standards to monitor ELL students' development and educational services (Wiseman & Bell. 2021). Consequently, ELD educators lack the necessary instructional and behavioral data collection and analyzation tools, training, and strategies to progress student learning and development (Fowler & Brown, 2018; Wiseman & Bell, 2021), demonstrate accountability to federal educational entitlement policies (Garver, 2022), and make educated and appropriate instructional decisions (Dodson et al., 2021; Fernando, 2020).

The scores from national achievement data present a worrisome reality across the field of education, especially so for culturally and linguistically diverse students (Fowler & Brown, 2018). According to Wiseman and Bell (2021), national standardized assessments offer the only readily available educational insight available for ELLs in most states. Achievement data continues to demonstrate a significant racial-ethnic achievement gap (Fowler & Brown, 2018), and little is known regarding the education of ELLs due to the lack of additive instructional servicing data available for this underserved subgroup of students. Despite the legislation and policies for equitable education and teaching English as a second language (TESOL) best practices (TESOL, 2023c), limited research exists on educational data monitoring for ELLs in general education settings and additive instructional settings (Fowler & Brown, 2018; Wiseman & Bell, 2021). Furthermore, without data on the services being utilized with ELLs, the educational system cannot adequately differentiate instructional experiences or Opportunities to Learn (OTL) for the diverse learners in ELD additive instructional settings.

Statement of Inquiry

The United States educational system needs better educational data and instructional accountability for ELLs (Wiseman & Bell, 2021). Through the lens of Mandinach et al.'s (2006) Data-driven Decision Making (DDDM) framework, this quantitative correlational survey study aimed to explore the importance of data collection and analyzation practices for New Hampshire ELD educators. At this stage in the research, data collection and analyzation in ELD was generally defined as the way in which teachers: (a) compiled, organized, and documented ELD interventional learning opportunities with students, (b) used data in a meaningful way to guide instruction, and (c) created reports on the data collected effectively for the betterment of the students. DDDM was the process of identifying data, collecting it to be analyzed and interpreted, and using data to set goals to improve educational experiences (Mandinach & Schildkamp, 2021a).

The present study explored the outcome of the dependent variable of teacher self-reported data collection and analyzation, and teacher-perceived importance of data through a cross-sectional survey and correlational analysis, using the length of teaching experience as the independent variable in the measurement of covariation. Correlational research aims to determine whether a relationship exists between two or more variables (Creswell, 2017). If a relationship was established between the variables, ELD standards could be evaluated and better informed by the current data collection and analyzation practices in three New Hampshire school districts. With accurate, higher quality, and meaningful data, the DDDM framework and research suggested that instructional quality likely increased to positively impact student achievement (Dodman et al., 2021; Dunn et al., 2013; Evans, 2015; Fowler & Brown, 2018; Gesel et al., 2021; Kurilovas, 2020; Mandinach et al., 2006; Mandinach et al., 2015; Mandinach & Schildkamp, 2021a; Mandinach & Schildkamp, 2021b; Visscher, 2021), offering exponential benefit to a subgroup of struggling ELLs (Fowler & Brown, 2018; Garver, 2022; Wiseman & Bell, 2021).

Research Question and Hypothesis:

The research questions were adapted from the literature by Zigmund (2020). The research questions addressed by Zigmund explored the data practices used by a population of educators in Pennsylvania Public Schools. This research study will focus on the data collection and analyzation practices of educators in ELD programs in New Hampshire. This study addressed the following questions:

1. What types of data do English language development educators report collecting and analyzing to modify instruction for English language learner students?
2. What relationship exists between the number of years an educator has taught in an English language development program and how the educator reports collecting and analyzing data to modify instruction?
3. What relationship exists between the number of years an educator has taught in an English language development program and the way in which the educator reports on the *importance* of collecting and analyzing data to modify instruction?

Based on these research questions, the research will attempt to disprove the following null hypotheses:

$H_0 1$: No statistically significant relationship exists between an educator's years of experience teaching in an English language development program and the types of data collected and analyzed to modify instruction.

$H_0 2$: No statistically significant relationship exists between an educator's years of experience teaching in an English language development program and the self-reported importance of data collection and analyzation practices used to modify instruction.

Research Methodology

The exploratory quantitative correlational study design, situated in the positivism and transformative paradigms, investigated the strength of the association between teaching experience in ELD programs and data-driven decision-making. A research paradigm combines research ontology, epistemology, and methodology and directs a study. The positivism paradigm examines a single reality through the relationship between two variables (Creswell & Creswell, 2018). The transformative paradigm is more concerned with examining the political change agenda to combat the societal oppression of marginalized groups (Creswell & Creswell, 2018). The researcher was naturally drawn to the transformative paradigm because of the possible equity restoration in the outcome of transformative research. Evidence of the blended paradigm was demonstrated through the correlational research methodology exploring the inequity that minimal data collection and analyzation creates in the ELD program for the marginalized subgroup of ELLs.

The survey data for the present study were collected from a range of ELD teacher participants using a voluntary response sample, considering Thomson et al.'s (2005) Quality

Indicators for correlational research. According to Thompson et al., the quality indicators used to assess correlational studies are split into four categories: measurement, practical and clinical significance, avoidance of common analytic mistakes, and confidence intervals for score reliability coefficients. Following the research design elements utilized by Lebron (2011) and Zigmund (2020), careful considerations were made regarding implementing the correlational research using the survey tool in public school settings. Additionally, Ruel et al.'s (2016) recommendations for quality surveys demonstrating validity and reliability were used to vet the instrument and survey implementation. According to Ruel et al. (2016), a survey research design is a procedural data collection system. A cross-sectional survey collects data at a single point in time to investigate current attitudes, beliefs, opinions, or practices (Creswell, 2017). The goals of the present research survey were to explore the relationship between multiple variables as they pertain to current data collection and analyzation practices. The self-reported survey collected data on teachers' years of experience teaching in an ELD program, utilization of different types of data collection and analyzation practices, and perceived importance of these types of data collection and analyzation practices. The survey can be found in Appendix A.

Setting: The structural context of this study was ELD programs operating under the United States Department of Education, Every Student Succeeds Act (ESSA) and Title III programs. This study occurred in those public school districts in New Hampshire, with an English language development (ELD) program, many of which are supported by Title III funding. The school districts with the state's highest demographic of the subgroup of students learning English as a second or subsequent language were sought after for endorsements first. The following chart provides information on the ELD student enrollment in these school districts with the highest ELD enrollment. Any district with 10% or greater ELD enrollment will be referred to as a *high-incident* school district.

Table 1

Total ELD Enrollment in Public School Districts For 2021 - 2022 School Year

Districts	Total Enrollment	ELD Eligible and Monitor	Ratio	Total ELD Endorsed Teachers
District A	4079	324	8%	15
District B	10138	1441	14%	79
District C	12428	2254	18%	88
New Hampshire	168620	6565	4%	606

(NHED, 2022)

As displayed in Table 1, the intended participating districts had a higher ratio of ELLs than the state average. These three districts with the highest ELL enrollment were sought for endorsements; however, low voluntary enrollment in the present research study resulted in the research opening participation to all willing and able ELD teachers in public school districts in New Hampshire.

Population and Sample: The present study featured 43 ELD teacher participants from the New Hampshire public school districts. Due to the accessibility issues of studying the national ELD scope, the unit of analysis was the target population of ELD educators in New Hampshire enrolled within the broader Title III, ELD population nationally. Participation was a non-probability convenience sampling, using ELD educator employment at a New Hampshire public school district as the primary qualifier and availability and willingness to complete the survey instrument (voluntary response) as a secondary qualifier.

After written notification was sent to the desired school districts, the researcher met with two of the largest districts to discuss the research study. Approximately 50 potential participants received the study introduction and invitation by email through their school district email account, endorsed by their district's director of ELD program. This pool of participants was less than the intended participant pool of 182 ELD teachers because only current ELD teachers were included in the research. The original number reflected teachers with dual certifications who might not be currently teaching as ELD teachers. To reach the desired sample size, mitigations were made by utilizing the NHED i4SEE certification list of ELL educators to obtain a sample pool. Direct emails were sent from the researcher to approximately 20 potential participants. The sampling frame was approximately 70 ELD teachers from across New Hampshire.

Based on the G*Power analysis of a point biserial model, two-tailed correlation with an effect of 0.5, the desired sample size was 42 participants. According to a meta-analysis of 1071 online surveys, Wu et al. (2022) contended that the average response rate for online surveys was 44.1%. The rate increased when surveys were clearly defined and the population was refined (Wu et al., 2022). Considering the original sample pool of 182 potential participants from the high-incident school districts, the survey response rate required would have been 23%, which was well below the average of 44.1% (Wu et al., 2022). For this study, the sample pool of 70 potential participants produced 43 respondents, establishing a 60% response rate. The participant sample was likely more active and engaged teachers based on their willingness to take the time to complete the survey instrument. All teachers provided voluntary consent to participate before completing the survey. The identities of the teacher participants and districts were kept anonymous, as the survey does not maintain any personal or identifying information. The survey administration specifications are outlined further in the following section.

Research Instruments, Variables, and Procedures

The correlational survey design was utilized to demonstrate the ways in which the independent variable related to the dependent variable, or affected variables (Creswell, 2017). The independent variables were years of experience teaching in an ELD program (continuous), and the dependent variables were (a) types of data educators use to modify instructional practices (categorical), (b) types of data analysis techniques educators use to modify instructional practices (categorical), and (c) educator perceived importance of data collection and analyzation. The following sections outline the data collection processes, procedures, and instruments used in the present study.

Instrumentation

A survey was the optimum collection method in this study. The present correlational survey design methodology was a quantitative cross-sectional survey measuring nonrandom groups (Ruel et al., 2016) with a descriptive statistical approach (Creswell, 2017). According to Ruel et al. (2016), Fowler (2014), and Creswell and Creswell (2018), surveys prove to be an extremely efficient and effective method of measurement, especially when the survey has a "...proper design, representative sampling, and appropriate and effective administration" (Ruel et al., 2016, p. 2). When considering social and behavioral science research methods, surveys offer "...a description of trend, attitudes, and opinions of a population" (Creswell & Creswell, 2018, p. 147) with flexible options in instruments and data collection (Ruel et al., 2016). Ruel et al. explained that surveys could be used in causal or experimental research. As in the present study, a causal research survey aimed to determine factors influencing the dependent variable. The survey instrument was a modified version of Zigmund's (2020) scale, designed and validated by

Cronin (2001), and used by Lebron (2011) and Wright (2006). The modifications are explained thoroughly in the following sections.

This topical survey was the preferred research approach for the present study based on generalizability, access to the target population through a brief and confidential snapshot, and using an instrument with fewer constraints than other research design elements. Self-administered surveys require careful wording, layout, and explanation because participants respond individually to the anonymous questionnaire (Ruel et al., 2016). Due to cost-effectiveness and accessibility to the target population, self-administered surveys are considered a highly valuable research instrument (Creswell & Creswell, 2018). To select a survey instrument for this study, the researcher considered the widely accepted ethical standards for human studies (justice, beneficence, and respect) outlined in the guidelines and standards of the Belmont Report from the National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1979). The survey was administered virtually, as technology increases the efficiency and accuracy of the data collection process (Ruel, 2016). The benefits of an electronic survey administered online are plentiful (Creswell & Creswell, 2018; Fowler, 2014; Ruel, 2016). Zigmund's (2020) survey instrument was adapted to the virtual platform of Google Forms, which was easy to self-administrate and at no cost to the researcher. Additionally, the Google Form survey dataset was simple to export to a Google Spreadsheet for data analytics.

Ruel et al. (2016) explained that "...the quality of data you get from the survey is only as good as the survey that produced them. Thoughtful design and formatting of the survey instrument are essential to reduce error as much as possible" (p. 25). Respondent burden, or the degree of stress, complexity, or ineffectiveness experienced by a research instrument, was a strong consideration when considering a survey (Ruel et al., 2016). Respondent burden potentially causes respondent fatigue and limits the efficacy of the results (Ruel et al., 2016). To minimize respondent burden and assess the measurement instrument, the adapted forms of the survey tool was modified for simplicity in multiple research studies, including Zigmund (2020), Lebron (2011), and Wright (2006).

Survey. The survey instrument was initially designed and validated by Cronin (2001) to explore a group of Connecticut principals' data usage. The instrument was later modified by Lebron (2011) to include teachers' data collection and analytics in Illinois and by Zigmund (2020) to investigate teachers' data use by Pennsylvania teachers. Cronin (2001) used a three-part process to develop *A Survey to Assess Data Use in Educational Decision-Making,* incorporating current literature on school improvement/planning, Total Quality Management, and data-driven decision-making. The purpose of *A Survey to Assess Data Use in Educational Decision Making* was to determine the data used by educators to develop measurable educational goals and improvements.

For this study, the researcher modified the most recent version of the survey in three ways: (a) three questions were added about ESSA demographics (question 5); English language proficiency WIDA assessment data usage (questions 8a and 8b); and data reporting (question 29); (b) use of clarifying wording such as "Title III" and "English language development"; and (c) three extension questions in conclusion. Restructuration of the survey question structure from individual questions into labeled 2-part pairs (a/b) provides a clear structure to the established survey. Additionally, section four was omitted from the survey for this study, as this section investigated educators' experience in data-focused professional development activities, which was not a primary variable explored in this study. The adapted survey administered in this research study, and the permission for the modifications are included in Appendix A and B, respectively. Zigmund's survey consisted of 54 questions split into five sections. The modified survey, which contained 54 questions and six sections, is outlined below.

- Section One included the title and study information.
- Section Two included a consent statement with a yes-or-no checkbox. This preliminary question was not included in the survey question count.
- Section Three (Questions 1- 6) included demographic information. Section Three will now have six questions. Question five was added for educators to respond regarding their school district's participation in Title III programming. The wording of questions three and four was modified with the words "English language learners" for clarity.
- Section Four (Questions 7 – 20) identified the types of data and the importance of data when making instructional decisions.
    - Outcome data (Questions 7 - 15, each with two parts)
    - Perception data (Questions 16 - 18, each with two parts)
    - Instructional process data (Questions 19 - 20, each with two parts)

  Modifications were made to the wording in this section. Wording such as "additive instructional services" and "English language development" was added to describe the data in question. Clarifications were also included for multiple questions with examples of the type of data being referred to. Some structural modifications were made to clarify the questions. Each question had two parts, i.e., data type with a yes or no checkbox response and a second question about the perceived importance of that data type. The first part of each question (data type) was referred to as part (a), and the second part of each question (importance) was referred to as part (b).

- Section Five (Questions 20 – 29) identified data analysis and the importance of data analysis when making instructional decisions. This section was also modified to include descriptive wording as outlined in section four to specify the data type the questions were referring to. An additional question (question 29) was included using the same wording pattern as the original survey. The intent of question 29 was to explore the reporting if any occurs with the data analytics. Section Five contained questions 20-29, with each question divided into a part (a) and part (b).
- Section Six (Question 30-31) were open-ended, short-answer, extension questions about the teacher's modes and methods currently in practice for data collection and analyzation during instructional decision-making and professional learning experiences. The open-ended questions were modified from Zigmund's (2020) original question to bring less emphasis to technology, but rather, for teachers to be given a space to describe their data collection and analysis strategies freely.

With the modifications, the questionnaire was 31 questions in length. Throughout, a five-point Likert scale was used for importance ratings for the current and modified scales (Zigmund, 2020). The researcher determined that the survey should take approximately 15 minutes to complete. When considering the addition of the four questions, the survey instrument utilized the wording and pattern of questioning as the previously vetted sections.

The survey had previously established content validity (Cronin, 2001; Lebron, 2011; Zigmund, 2020) which identified that the items measure the content they intend to measure (Creswell & Creswell, 2018). The original survey was reviewed in the creation process by two instrument design experts and ten experts representing the academic, national, state, and local data-driven decision-making perspectives. The survey was developed under expert supervision and a Survey Review Group of 30 - 40 principals for readability, content, and ease of completion. Next, "proportional stratified sampling was utilized to ensure that the proportion of each subgroup in the sample (elementary, middle, and high school principals) was the same as their proportion in the population" (Cronin, 2001, p. 12). Validity and reliability were demonstrated through proportional stratified sampling, as well as the data analysis through descriptive statistics for each item.

According to the quality indicators by Thompson et al. (2005), measurement was the reliability and validity of a tool or study procedure to measure what the researchers intended to examine. Thompson et al. reported on the importance of including reliability coefficients of the scores in a correlational study to strengthen the reliability of their data analysis. After the creation of the survey instrument, Cronin (2001) determined that the survey results established the need for an expanded pilot study. Cronin explained the validity and reliability process:

> The survey data was then used to frame questions that were asked during the nine structured interviews. These interviews were then analyzed for recurring themes and ideas. Data from the interviews was then sorted and coded according to the research question it addressed. A critical reviewer was used throughout the data-analysis process to protect against researcher bias. (p. 13)

This process provided a foundation of validity for *A Survey to Assess Data Use in Educational Decision-Making* to be used in this research study.

Data Collection Procedures. This research study included New Hampshire school districts, or local education agencies (LEAs). High-incident school districts were chosen based on the total subgroup enrollment of ELLs. ELD educators received similar professional development, assessments, and ESOL directives under the supervision of the New Hampshire state educational agency (SEA) EL Education Consultant. Superintendents from the three high-incident school districts were contacted in December 2022 with an email request for participation approval of the district's ESOL educators. The email included an introduction to the survey, which was attached in Appendix C. Two of the districts sent an endorsed email to their ELD teachers. The researcher also provided a study explanation and invitation directly to the published email addresses of ELD educators listed on the NHED ESOL endorsement list.

Participation emails began distribution on January 11, 2023. The researcher intended for the survey to remain open for a two-week response deadline. However, not enough participants were enrolled by this deadline, so the survey remained open for 31 days to meet the participant threshold. Forty-three participants completed the research study. After the original email was sent, a maximum of two reminder emails were sent on days 4, 9, and 12 with clear and simplified messages about the survey's intentions and research. A sample endorsement letter for district use was supplied and presented in Appendix D.

Data Analysis Procedures. Data analysis began by exporting the Google Forms survey responses to Google Sheets. The data was cleaned for mistakes, organized, and sorted into multiple data sheets for inferential computation, including assigning a numerical value to all the nominal data (i.e., Likert responses and yes/no questions). Scores were assigned to the dependent variables based on the sum of responses from Sections Three: Data Collection and Sections Four: Data Analysis. The descriptive statistics, variability, and measures of central tendency were calculated first. The significance was set at .05 as commonly accepted. Salkind and Frey (2020) highlighted the importance of the mode calculation for nominal data, such as the nominal frequency categories (yes or no) used in the dataset. The inferential statistic calculations began by conducting the Pearson product-moment correlation coefficient (*r*) for the relationship between the variables in multiple combinations:

- Years of teaching ELD and data collection score sum
- Years of teaching ELD and data analyzation score sum
- Years of teaching ELD and importance of data collection score
- Years of teaching ELD and importance of data analyzation score

The Pearson product-moment correlation coefficient (*r*) is a parametric calculation for the circumstance where the independent and dependent variables are both continuous.

The nonparametric, point biserial correlation coefficient (r_{pb}) was used for the continuous independent variable (years teaching in an ELD program) and categorical dependent variable (types of data teachers collect to modify instructional practices and types of data analysis techniques teachers use to modify instructional practices). The tests were all conducted in the Google Sheets. To conclude the data analysis process, Questions 30 and 31b, open-ended reflective questions, were analyzed for themes and trends using inductive data analysis (Creswell, 2017). Saldaña (2021) explained that descriptive coding techniques are used to derive descriptive measures from the themes. The following themes were analyzed in the first phase of coding: *data collection techniques*, data analyzation techniques, *data collection importance*, *and data analyzation importance*. Saldaña's focused coding was used for a second cycle of coding to bring further clarity and emphasis to the themes and visualizations. All qualitative codes were analyzed and presented quantitatively.

Ethical Issues in the Study

By design, all ESSA programs are concerned with bettering the educational opportunities of sensitive, marginalized, or disadvantaged students (Vail, 2022). Title III and ELD are specifically concerned with the educational equity of ELLs. A potential power imbalance existed, and exploitation concerns needed to be considered when working with ethnic groups usually qualified for ELD programs, such as refugee and immigrant students (Duff, 2014). While marginalized student data was a central currency in this study, teacher participants did not utilize the individualized student data, but rather the aggregate data regarding ELD teacher data collection and analyzation, and how they fit in the whole.

Another ethical concern was the collection of data with possibly harmful perceptions. The investigation of this study was the exploration of the current practices of data collection and analyzation in ELD programs in New Hampshire. If the participants responded about their lack of data usage, then a potential perception could be created about the lack of professionalism of ELD teachers (Irizarry, 2009), but also an exposure of the dire need for the exact ELD data practice, which are central to this present study.

Assumptions

From the perspective of an ELD teacher who has taught in multiple instructional settings with ELLs for over ten years, the researcher experienced the lack of an adequate and synchronized data collection and analyzation method firsthand. Over the years, the researcher attempted to collect and use student data from many sources to provide systematic and comprehensive reports and to guide instructional practices. This study was born from the researcher's anecdotal concern regarding the lack of ELD data being used and reported across New Hampshire. The following were the epistemological assumptions behind the present study:

- Teachers needed a better system of servicing data collection and analyzation
- ELD educators lacked data efficacy
- Data reports should be easy to access and useful
- Data was necessary for better, quality instruction in ELD and Title III servicing programs
- Record keeping for daily instructional opportunities was lacking in the field of education, especially in ELL educational subgroups
- Technology was the future of data collection

Based on these assumptions, this study explored the current systems of data collection and analyzation in ELD. This study could be a useful tool for LEAs as school district administrators attempt to understand ELD and Title III better. These foundations can lead to more funding and better accountability for SEAs, but also can have national implications for ESSA programs, special education, and other specialized educational subgroups.

Limitations and Delimitations

Creswell (2017) described limitations as external flaws to the research study. While the present study offered knowledge and findings on ELD educators' data practice in New Hampshire school districts, the nature of ELD program and ESSA: Title III politics tends to be complex (Garver, 2022; Skinner, 2019). For example, the federally governing program for many ELD programs, Title III, accountability has not been evaluated since 2010, and ESSA proved to be very private about the systems being utilized (Garver, 2022). Section Two will provide a full organizational background and national and state educational operations analysis. While the ELD programs are overdue for a data revival, the political structure and framework surrounding the topic presented a limitation that cannot be ignored.

Other limitations of this research study included the internal validity of the self-administered survey design, sampling bias, and response rate and accuracy. Fowler (2014) divided survey research errors into two categories: errors with who answers and errors with the answers. In reference to the survey instrument being utilized, these potential errors were considered and addressed for the present research. Parameters around the sample pool certification and participation in ELD programs mitigated the error of who answered the survey. Still, the following limitations still existed. Ruel et al. (2016) discussed concerns over the limitations of the survey design based on threats to internal validity. The survey instrument utilized was self-administered, which had the potential of skewed responses for the topics that are less understood due to the limited understanding of the terminology, such as *Title III* and *data collection and analyzation* in the context. The chosen survey limited potentially confusing acronyms and terms to ensure more reliable response data. By nature, the survey design determined the generalizability of the population based on the answers of a portion of the population (Ruel et al., 2016). Thus, overly positive or negative response bias could make the data effect greater or smaller. For this reason, sampling bias was considered a limitation.

The rate and accuracy of participant responses were also in question. The participant response rate of the survey was a limitation. While the researcher chose the survey design, the ELD educators who participate and complete the survey are out of the researcher's control. In reference to accuracy, Rowan et al. (2004) determined that teachers are highly inaccurate in their ability to self-reflect and recall the behaviors they do most frequently and infrequently. For example, teacher reflections will likely be highly inaccurate if asked about the data collection that rarely occurs. Fowler (2014) identified the same phenomenon, social desirability, and described ways to minimize the effects, such as minimizing judgment and providing confidentiality or anonymity measures. Ruel et al. (2016) described two standard errors of retrospective questions: frequency, telescoping error, and recall loss. Similar to Rowen's teacher recall [in]accuracy, a telescoping error is the "tendency for respondents to remember things as happening more recently than they actually happened" (Ruel et al., 2016, p. 71). Recall loss refers to a respondent forgetting something that occurred altogether (Ruel et al., 2016). Ruel et al. recommended limiting retrospective questions as these questions can produce "time frame overload" (Ruel et al., 2016, p. 71). These recommendations were considered heavily in selecting the survey instrument to mitigate the effects of the limitation on the results.

Delimitations are the researcher's choices that inherently limit the study (Creswell, 2017). Two design delimitations were identified: choice of LEAs and research methodology. Selecting LEAs was a thoughtful and intentional process, reflective of the district's ELL demographics and leadership receptiveness to new ideas. One of the elements of a dissertation in practice was for the researcher to perform the research in their own environment (Tamim & Torres, 2022). Therefore, the researcher chose to limit this study to the state of New Hampshire, despite the relatively small ELL population (Office of English Language Acquisition, 2021b), as compared to other states, such as New Mexico, California, Texas, and Arizona (Jimenez, 2022). The primary LEAs chosen for this study were amongst the districts with the largest ELL populations in New Hampshire (NHED, 2022).

Another delimitation was the choice of the survey as the research methodology for this study. Surveys are a highly effective quantitative research design element that offers considerable generalizability (Ruel et al., 2016; Fowler, 2014; Creswell & Creswell, 2018). Compared to interviews and focus groups, a survey can reach a greater pool of participants. The survey chosen, *A Survey to Assess Data Use in Educational Decision Making,* had demonstrated reliability and validity for the purpose of exploring data collection and analyzation (Cronin, 2001; Lebron, 2011; Zigmund, 2020). This tool was an asset in exploring the data practices of ELD teachers, despite the limitations and delimitations presented regarding survey research.

Significance and Summary of the Inquiry

DDDM may have a significant impact on local school systems (Ikemoto & Marsh, 2007; Mandinach et al., 2015; Young et al., 2018), but an insufficient understanding of the data collection and analyzation for the student subgroup of ELLs was prevalent in the educational system (Fowler & Brown, 2018; Wiseman & Bell, 2021). This study contributed to scholarship and practice by providing a snapshot of the current data collection and analyzation status in ELD programs in New Hampshire. While ample evidence existed to support the ESSA: Title III initiative and ELD purpose (Boyle et al., 2010; Birman & Tran, 2017; Chu & Fong, 2015; OELA, 2020a), the lack of research available on the current data practices being provided ELD programs in public schools was alarming (Fowler & Brown, 2018; Wiseman & Bell, 2021). The findings from this study provide SEAs and LEAs with the understanding of current practices necessary to elevate their data collection and analyzation standards and verify that the needs of ELLs are being met on a large scale.

Definitions of Key Terms

The following are standard terms that will be used in the present study;

Additive Instructional Services or Additive Instructional Settings: *Instructional subgroups for students with academic or linguistics gaps with a specialized teacher in a smaller, individualized context. In ELD, these groups are often called push-in/pull-out groups or intervention supports (Garver, 2022, Kurz et al., 2015)*

Annual Measurable Achievement Objectives (AMAOs): *Under Every Student Succeeds Act (ESSA), Local Education Agencies (LEA) are required to establish Annual Measurable Achievement Objectives (AMAOs) for the English language acquisition and academic achievement of limited English proficient (LEP) students (Boyle et al., 2010)*

Adequate Yearly Progress (AYP): *Under Every Student Succeeds Act (ESSA), Local Education Agencies (LEA) are required to establish Adequate Yearly Progress (AYP) goals for the English language acquisition and academic achievement of limited English proficient (LEP) students (Villegas & Pompa, 2020).*

Data-Driven Decision Making (DDDM): *The use of students' performance data to inform educational decisions (Buzhardt et al., 2020; Mandinach, 2012)*

Data Efficacy: *teachers' attitudes, abilities, and beliefs about their data collection, analyzation, and reporting ability (Bandura, 1997; Dunn et al., 2013)*

Data Wise: *The Harvard Graduate School of Education eight-step educational data improvement process guiding teams to work collaboratively to improve teaching with data and evidence-based analysis (Boudett et al., 2015)*

Educational Equity: *Fair exchange of personal or social circumstances in educational settings where obstacles are eliminated so all students can achieve their full educational potential and basic minimum level of skills (Adams, 1963)*

English for Speakers of Other Languages (ESOL): *Common term for the learning environment for students whose English is not their primary or first language. English for speakers of other languages (ESOL) or English as a second language (ESL) (Holfester, 2021; Estrada et al., 2020)*

English Language Development (ELD): *Current term for the learning environment for students whose English is not their primary or first language. Previously English for speakers of other* *languages (ESOL) or English as a second language (ESL) (English language development, 2019)*

English Language Learner (ELL): *Student who is learning English as a subsequent language to their first or primary language (Holfester, 2021)*

Every Student Succeeds Act (ESSA): *The 2015 United States federal K-12 education law which replaced the "No Child Left Behind" law. ESSA is more flexible with States and provides more transparency for parents and for communities (Skinner, 2019)*

Intervention Group: *student grouping, either in or out of the classroom in an educational setting where a teacher provides learning opportunities intended to build knowledge or skill, usually for ELD, speech language pathology, reading or math support, etc. (Education Law Center, 2016; Education Law Center, 2022)*

Local Education Agency (LEA): *Local educational agency is the "public board of education or other public authority legally constituted within a State for either administrative control or direction of, or to perform a service function for, public elementary or secondary schools in a city, county, township, school district, or other political subdivision of a State, or for a combination of school districts or counties as are recognized in a State as an administrative agency for its public elementary schools or secondary schools" (34 CFR 303.23(a)) (Local Education Agency, 2017)*

No Child Left Behind Act (NCLB): *United States federal K-12 educational accountability law from 2002-2015 and replaced by Every Student Succeeds Act (ESSA). This law introduced Title I provisions for struggling students (Skinner, 2019)*

Opportunity to Learn (OTL): *Inputs and processes within an educational context intending to produce higher student achievement outcomes. The core components of OTL are instructional time, content, and quality of instructional time (Kurz et al., 2014)*

State Education Agency (SEA): *The state-level government organization within each US state responsible for education, including providing information, resources, and technical assistance on educational matters to schools and communities (Skinner, 2019)*

Teaching English to Speakers of Other Languages (TESOL): *Another term for an English for Speakers of Other Language (ESOL) program and the task of educating in such a program (Holfester, 2021; Estrada et al., 2020)*

Title III: *Division of the Every Student Succeeds Act (ESSA) dedicated to bettering the education of students who are English language learners, or immigrants to the United States (Boyle, Taylor, Hurlburt, & Soga, 2010)*

World-Class Instructional Design and Assessment (WIDA) Consortium: *Association including 41 states using high-quality standards and instruction to support ELLs in academic language development to promote achievement for culturally and linguistically diverse students (WIDA, 2022)*

Contributions to Scholarship and Practice

The achievement gap for culturally, linguistically, and ethnically diverse students has posed a great concern for decades (Beecher & Sweeny, 2008; Fowler & Brown, 2018). Still, the only data being recognized was standardized test scores (Wiseman & Bell, 2021) and a single yearly English language proficiency assessment (WIDA, 2022). The Every Student Succeeds Act (ESSA) required state legislators and policymakers to diligently create new assessment and data criteria for public schools (Garver, 2022; Fowler & Brown, 2018; Wiseman & Bell, 2021).

Furthermore, data is a meaningful, proven tool to inform decisions (Mandinach & Schildkamp, 2021a; Shaked, 2010), yet ELD has a chasm in place of basic educational data (Fowler & Brown, 2018; Wiseman & Bell, 2021). Shaked (2010) emphasized that “what gets measured gets noticed,” but ELD seems to be one of the only educational settings lacking metrics. The trend of bringing justice to marginalized people only exacerbated the fact that there are limited to no servicing data collection and analyzation reports of the learning opportunities our educational system was providing to ELL students in additive instructional settings or interventions. This study was a starting point to investigate what data was being collected and analyzed as a measurement tool for where the educational system might improve.

SECTION TWO

ORGANIZATIONAL ANALYSIS

Organizational theory is a method of explaining the complex systems and principles at play in the workplace, including "scientific explanation, human understanding, and artful appreciation... [while creating] possibilities for effectively designing and managing organizations" (Hatch, 2013, p. 5). Frames give structure to better comprehend the complexities of organizations (Morgan, 2006; Hatch, 2013; Bolman & Deal, 2017). Hampden-Turner (1992) addressed the necessity of frames, "[humans] cannot begin to learn without some concept that gives you expectations and hypotheses" (as cited by Bolman & Deal, 2017). Bolman and Deal (2017) described a frame as a mental model of assumptions and ideas, defining questions and optional solutions. As problems arise, many leaders might be tempted to solve the problem from their current frame of perception, rather than reframing their understanding based on the complexity of the problem and how the problem is situated in the organization (Bolman & Deal, 2017; Hatch, 2013). Additionally, Hatch explained how understanding the multiple frames brings to light the assumptions behind actions and the development of ethical awareness. By analyzing organizations with different perceptions or frames, a person can develop a better understanding of past actions, assumptions that drive decisions, and the best plan for future changes and challenges that might arise.

In addition to the physical setting of the New Hampshire school districts, the present research study is situated in the organizational context of the broad and complex system of the United States Department of Education (USED) from the national to the state level. The background of the USED will be discussed, as well as the New Hampshire Department of Education (NHED) state educational agency (SEA). Next, this chapter will examine how the organizations are situated, based on Bolman and Deal's (2017) frameworks and the influences of the assumptions within each framework. Additionally, a leadership analysis has been prepared for the organizations being studied. After the review, a reflection on the implications of completing the present research in this setting will be provided.

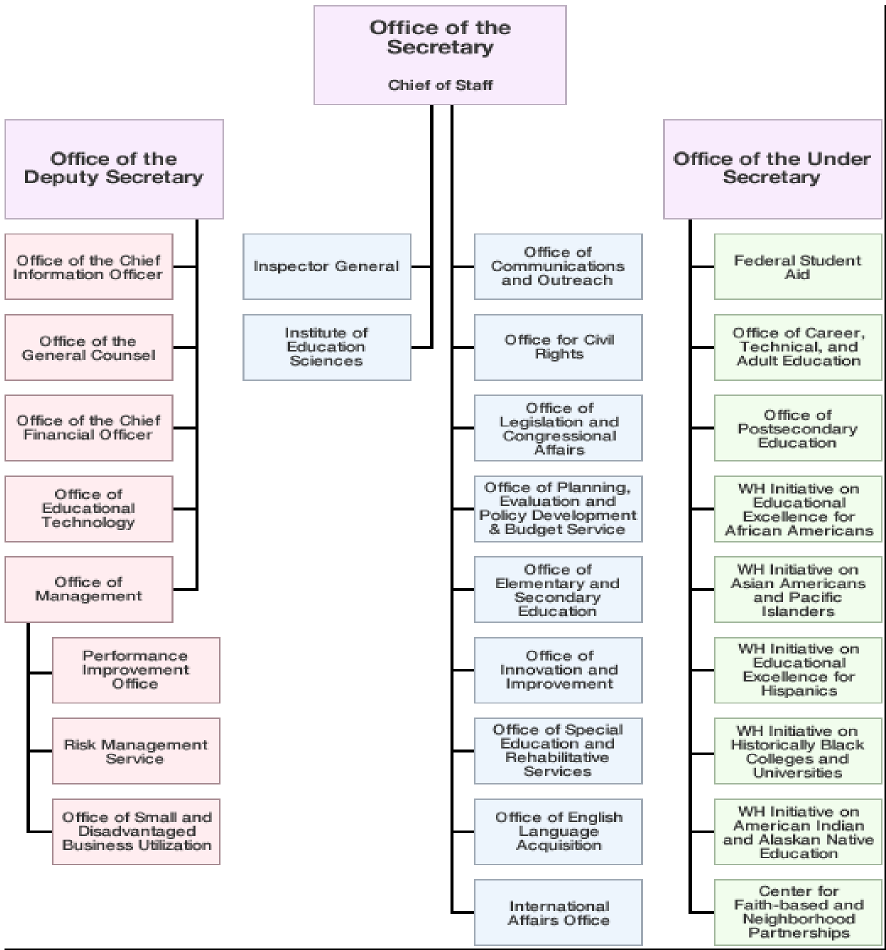
Organizational Background

The USED is a cabinet-level organization, first created by President Andrew Johnson in 1867, but was demoted a year later due to concerns about control (USED, 2018). Over the next 50 years, the idea of an educational department took many forms and names until the ED that we know was established in 1979 by President Carter (USED, 2018). In 1979, the USED employed 3000 staff members and had a budget of $12 million (USED, 2018). In the 2023 President's present budget, a USED discretionary budget of $88.3 billion was requested, compared to the enacted 2022 budget of $476.4 billion (USED, 2022a). The department employed 3912 staff members in 2018 (USED, 2018). In 2021, Dr. Miguel A. Cardona was named the Secondary of Education, and the 12th leader of the USED (USED, 2022a; USED, 2021). In 2022, USED had three departments: Office of the Secretary and Deputy Secretary, Deputy Secretary, and Under Secretary (USED, 2022b).

Regarding the growing population of multilingual learners, two offices are primarily concerned with the education of English language learners (ELLs): the Office of Elementary and Secondary Education and the Office of English Language Acquisition (OELA). The Office of Elementary and Secondary Education has considerably more emphasis on the education of ELLs since the Every Student Succeeds Act (ESSA) operates from this office. The following figure is an organizational map of the USED.

Figure 1

Organizational Map of USED



(USED, 2022b).

ESSA

President Obama signed ESSA into law in 2015, but the United States Educational Secretary and Deputy Secretary oversee the daily affairs. According to Skinner (2019), ESSA was the reauthorized version of the Elementary and Secondary Education Act (ESEA) from 1965, which was previously amended as No Child Left Behind (NCLB). Due to the neo-libric nature of the No Child Left Behind act (2002) and ESEA, data collection for education began to grow in popularity during the early 2000s (Dodman et al., 2021; Evans, 2015). The USED delegates most of the decision-making capacity to State Educational Agencies (SEAs), which is why the setting of this research is housed in the SEA of a New England state. In 2021, ESSA programs were allocated $26.4 billion to improve the quality of the educational system in schools across the nation at the state level (NEA, 2020).

The overarching goal of ESSA is to distribute more resources, funds, knowledge, and freedom into the lowest income educational systems to supplement existing programs. However, the existing guidance is a labyrinth, outdated and confusing (Gordon & Reber, 2015). With some updates, under ESSA, states were given more flexibility in developing accountability systems, but these systems were required to include "...content and academic achievement standards and aligned assessments in reading/language arts, math, and science for specific grade levels" (Skinner, 2019, p. 1). These systems were also required to include "(1) long-term and interim performance goals for specified measures; (2) weighted indicators based, in part, on these goals; (3) an annual system for meaningful differentiation that is used to identify schools that need additional support to improve student achievement" (Skinner, 2019, p. 1).

School administrators are responsible for understanding the guidelines for how schools use ESSA funds compared to schools without these funds (Gordon & Reber, 2015). ESSA has compliance requirements, fiscal responsibilities, and an audit and accountability process if the accountability rules are not adhered to (Gordon & Reber, 2015). Furthermore, 13% of corrective letters in Title I require repayment (Gordon & Reber, 2015). Even after multiple modifications to Title I guidelines, the compliance was based on maintenance of effort, comparability, and supplement, not supplant. The administration determines how the funds will be used in Title I and with all ESSA programs. Gordon and Reber (2019) found that three-quarters of the schools used their Title I funds for personnel, with as much as one-third of funds being used for regular classroom teachers to lower class sizes. “States and districts try to best serve their students while adhering to these complex and evolving set of rules, devoting considerable staff time to documenting their compliance and formally associating particular expenditures with permissible titles” (Gordon & Reber, 2019, p. 143). Rowen and Correnti (2009) observed that well-intended educational policies were difficult to measure the effectiveness and determine a statistically significant connection between school quality and money spent. In fact, the limited data available failed to demonstrate the connection between costly interventions or initiatives and student achievement (Rowen & Correnti, 2009).

Title III

The specific ESSA programs for Title I, II, III, IV, V, and X provide guidance for different groups of students, including Title III, which endorses and funds academic programs for English language learners (ELLs) (Skinner, 2019). English language education is a student’s right ordered by the United States Supreme Court and codified in 1974 as the Equal Educational Opportunities Act (Garver, 2022) and the 1968 Bilingual Education Act, which funded English language education within LEA (Williams, 2020). NCLB continued the efforts through federal funding for the first Title III program dedicated to providing linguistic and academic equality for ELLs (Williams, 2020). Language Instruction for English Learner and Immigrant Students Act is the official name for Title III, a program that supports English Language proficiency (ELP), increases academic attainment, and aligns with the challenging state standards. When NCLB was reauthorized as ESSA, ELD accountability became shared between Title III and Title I (UnidosUS, 2018b). Opposed to a siloing of subgroups, the education of *all* students became the focus (UnidosUS, 2018b).

Organizational Analysis

The USED and SEA have very different organizational assumptions, which can be clearly reflected through the four-frame model by Bolman and Deal (2017). The westernized educational system includes many similarities across schools regarding the agenda as organizations in a frame model. The following analysis is an evaluation of the USED and SEA through Bolman and Deal's structural and political frames to better understand organizational components.

Structural Frame

In organizational analysis, the structural frame is heavily influenced by the roles, goals, strategies, and policies (Bolman & Deal, 2017). The broad goal of education is to shape developing minds and create functioning society members. "The central belief of the structural frame reflects confidence in rationality and faith that a suitable array of roles and responsibilities will minimize distracting personal static and maximize people's performance on the job" (Bolman & Deal, 2017, p. 47). The structural frame also emphasizes the completion of the task or goal (Bolman & Deal, 2017). The USED and SEA are situated in the structural frame. Success often comes back to metrics: standardized test scores, grades, and school ratings. In Title III, student achievement is predominately based on a students' English language proficiency (ELP), which is determined by an annual standardized, performance assessment (Fowler & Brown, 2018). Additionally, a hierarchical structure, another component of the structural frame, classifies the roles of politicians, administrators, stakeholders, teachers, parents, and students.

Another example of how the educational system resembles a structural frame, LEAs often use a predetermined curriculum, establish how the students will be serviced, and guide the localized education process. Authorities from LEAs, usually district-level administration, hold the power of most decision-making, rules, and policies. School-level and topic networks are created internally; however, they contribute as more of a task force towards the predetermined decisions made by higher-level administrators. Even though the instructional setting of education follows more of a human resource frame, the need and use of data to maximize effectiveness is a structural frame concept.

Two examples of major dilemmas in ELD are “underuse versus overload” and “differentiation versus integration” (Bolman & Deal, 2017, p. 73). In their own school settings, the researcher observed times of too little work followed by extreme overwork. Underuse occurs during the month of standardized ELP testing. Testing is technology-based, so the proctor must provide complete attention to the assessment, and cannot service ELP groups of students. During the entirety of the 2020-2021 school year, the researcher serviced a caseload of over 50 English language learners (ELLs) demonstrating an overload of instructional groups and the administrative tasks associated with ELD servicing (Education Law Center, 2016; Education Law Center, 2022; Oklahoma State Department of Education, 2007; The Campaign for Educational Equity, 2014). Maximum caseloads vary greatly, ranging from 15 students (Oklahoma State Department of Education, 2007) to 30 students (Education Law Center, 2016). As of 2022, the researcher has not experienced a caseload of under 30 ELLs.

ELD instructional model is another ELD decision directed by LEAs. The four main instructional models which LEA’s use in structuring programs for ELD are:

- Sheltered Immersion: All content areas for ELLs in English in an ELL-specific classroom
- Bilingual: Content and language instruction taught in ELLs primary language and secondary language simultaneously

- Pullout ESL: ELLs learn content in mainstream classrooms and English in smaller intervention groups
- Full Immersion: ELLs learn content and language in mainstream classrooms and can receive push-in support from an ESOL teacher

  (Holfester, 2021; Owens, 2020).

Ample research has been published supporting every ELD instructional options and strong biases exist for each option (Owens, 2020). Each instructional model creates a very different experience for the ELLs and ELD teachers. Some districts allow teachers to be autonomous, but others provide a specific curriculum to synchronize all instruction. Despite the rigidity of the structural educational system, ELD is a very complex field of education; therefore, some educational differentiation is necessary for best practice (Owens, 2020; Garver, 2022; UnidosUS, 2018b).

Political Frame

Power is the primary focus and agenda of the political frame. The USED and SEA are, by nature, political structures. USED, SEA, school board officials, school-level leaders, and LEA administrators are all influenced by the political framework mindset, as they are the decision-makers in the organization. Bolman and Deal (2017) describe politics as “the realistic process of making decisions and allocating resources in a context of scarcity and divergent interests” (p. 179). The assumptions in this framework begin and end with the limited resources available and the polarity of how these resources should be used. Funding is a prime example of a political decision brimming with educational assumptions in which the coalition’s individuals have varying interests and values. Bargaining and negotiating are how agendas come to fruition (Bolman & Deal, 2017).

Education has competitive energy around finding the best curriculums or initiatives (Schwartz & Diliberti, 2022). Schwartz and Diliberti (2022) found that initiatives in education create ample fatigue, but the chances of constant educational initiatives fading is unlikely as initiatives offer a flex of power and control. In many districts, school boards hold the most power and the best demonstration of the political frame in action. Portz and Beauchamp (2022) explained how ESSA's bipartite accountability system combined a school rating and accountability indicators, i.e., student achievement, graduation rates, etc. This accountability system is "the means by which policymakers, the public, and other 'account-holders' determine whether students, schools, and other 'account-givers' are meeting identified goals" (Portz & Beauchamp, 2022, p. 718). Government systems hold the power of determining accountability and compliance. The Center for Education Policy (2017) reported that 25 out of 34 SEAs had enough evidence and data to respond to the accountability indicators (as cited by Portz & Beauchamp, 2022). Portz and Beauchamp (2022) found four variables affected how policymakers approached accountability systems: economic, political, motivation, and instructional.

Another factor of the educational system as a political frame is how the ELL subgroup and their families are provided for under the ESSA and Title III programs. Many ELLs have limited access to resources (Wiseman & Bell, 2021; Jimenez, 2022). Since a political system's goal is to allocate resources, the educational system becomes the prime location to distribute equitable resources to frequently marginalized subgroups. Contrary to the authoritative political view of the superior race and gender acting as saviors to those 'lesser', the political frame has the power and authority to build systems that serve communities well (Bolman & Deal, 2017). Many non-English speaking families come to the United States educational system without understanding the educational supports available to students and their parental rights (Jimenez, 2022).

Leadership Analysis

While the USED and NHED leadership represent the top of the hierarchical stratification, the direct leaders working with ELD educators are at the LEA and school levels. Similar leadership structures are present in the three school districts involved in this study. Superintendents, assisted by assistant superintendents, chief officers, and ample support staff, administer the school district (Carpenter, 2022). Carpenter (2022) described the superintendents as the *managers*, providing instructional leadership, policymaking, and community liaison. Additionally, each district has a school board governing the educational system and working directly with the superintendents. Many school boards in New Hampshire districts range from nine to fourteen members, serving three-year terms, and some members are given a small yearly stipend. School board meetings are politically driven, and community members are encouraged to attend the meetings to provide input on school policies, budgets, and planning.

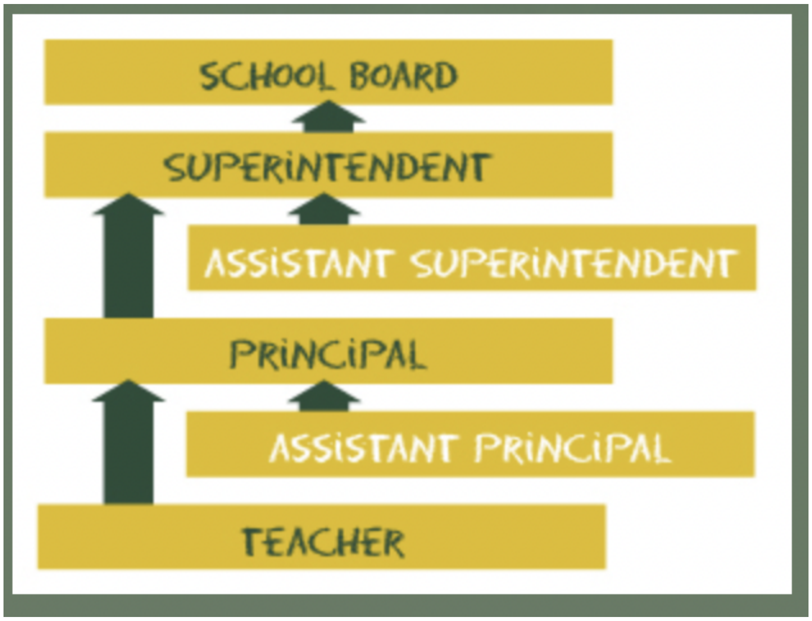
Ultimately, school district leadership and school boards are tasked with the equitable learning of all students. According to Aronson and Bartoletti (2016), educational leaders are charged "with equity and responsiveness and with cultivating a community of care and support for students that include infusing the school's learning environment with the cultures and languages of the school's community" (Dormer, 2016, p. v). In both the structural and political frames, leaders are more authoritative and directive in their leadership approaches. Like other school leaders, most superintendents participate in the structural support systems of unions for protection and guidance.

Through the researcher's anecdotal observation and prior conversations, educators in many New Hampshire districts expressed a lack of trust in their respective districts. One possible cause of this mistrust is the frequent turnover of district leaders. Multiple districts in this study have had new superintendents in the last year. Waters and Manzano (2006) compiled a meta-analysis of 2,817 schools examining the relationship between superintendents and student achievement. According to the meta-analysis, Waters and Manzano established three conclusions; district leadership matters, effective superintendents focus their efforts on creating goal-oriented districts, and superintendent tenure is directly related to student achievement. Carpenter (2022) identified the average superintendent tenure as one to five years. Schwartz and Diliberti (2022) discovered an alarmingly disproportionate number of superintendents are leaving the profession. Unsurprisingly, 95% of superintendents described an increased workload and stress (Schwartz & Diliberti, 2022). The recent lack in leadership tenure in multiple New Hampshire districts confirms these findings.

Principals are another influential element of school district leadership. The three sample districts examined in Section One: Table 1 had a total of 48 schools, and each school usually has at least one principal. Assumptively, at least 48 principals had a potential influence on the ELD teachers in the present research study. The following figure displays the hierarchical leadership structure in most school districts in the United States.

Figure 2

School District Leadership Structure



(My Texas Public School, 2022)

In educational leadership structures, principals are equivalent to the middle management of the organizational structure. Ample research is available about the leadership role of principals, including McLaughlin (2020), Schwanke (2020), and McArthur-Blair and Cockel (2018). McLaughlin suggested that the best principals did eight things:

1. Personalize data
2. Generate and promote equitable learning goals
3. Culturally proficient teacher selection
4. Increase culturally proficient instruction
5. Infuse highly structured interventions
6. Utilize student voice
7. Create a space for culturally diverse students

8. Partner with parents

Leadership styles vary, but the school-level principals and assistant principals selected for the present study had culturally diverse schools necessary for the cultural proficiency leadership strategies developed by McLaughlin.

Schwanke (2020) described a principal leadership reboot, implying the necessary upheaval of the current leadership system and practices. The author suggested eight leadership practices; rebrand, reconnect, reinvest, revamp instructional leadership, re-envision teacher potential, reframe data, revisit operations, and relax (Schwanke, 2020). Currently, principals across the educational system are experiencing major burnout (DeMatthews et al., 2021; Schwanke, 2020), which increases the challenge of being an innovative and transformational leader and the need for a "re-do" (Schwanke, 2020). McArthur-Blair and Cockel (2018) described the most innovative leaders as the people who can withstand challenges, "foster hope, sustain oneself during times of despair, and prompt forgiveness" (p. 126). This description is pivotal to Appreciative Inquiry (AI) leaders who are courageous with their team's assets to propel the organization forward (McArthur-Blair & Cockel, 2018). Inquiry-based leadership emphasizes and utilizes an individual's strengths and resilience which is incredibly powerful for team camaraderie, culture, and trust (Cooperrider & Fry, 2020). Even when challenges arise, AI principals and their teams ask questions to discover the path to success, which could be extremely effective in the educational system.

Implications of Research in the Practitioner Setting

The present study explores a problem of practice that was identified while the researcher was teaching in an inner city, public education setting, as an ELD servicing educator. The instructional model was immersive ELD, with *pull-out, push-in* additive instructional services provided by the ELD teacher. The researcher's caseload was well above the recommended maximum (Education Law Center, 2016; Education Law Center, 2022; Oklahoma State Department of Education, 2007; The Campaign for Educational Equity, 2014), with over 50 students, and the majority of EL students were being *pulled* for ELD service 2 to 4 times a week. Training, resources, or recommendations on ELD data collection and analysis were never offered to teachers in this school district. Structurally, the LEA leadership was either lassie-faire or authoritative. The problem of practice was illuminated within the organization, influencing the researcher to explore the USED and SEA's policies regarding data collection, analyzation, and reporting.

In the past, the researcher experienced LEA leadership violating federal law by making political decisions to defund and cancel ELD programs with little evidence or data supporting the change (EEOA, 1974). These changes were influenced by political agendas and greatly impacted the researcher's organizational assumptions. When the ELD programs were canceled, many teachers left the researcher's LEA due to the lack of data regarding the decision. The present study examines where the data disconnect occurs in the structural frame of USED in New Hampshire. Even though the instructional setting of ELD education follows more of a human and symbolic frame, the present research focused on the structural and political nature of Title III, and the broader, ELD initiative.

The structural and political frame likely affected the study participants and research findings. The structural frame likely affected the findings by emphasizing the relationship between the variables, while correlational research only explores the correlation. The structural frame influenced the researcher in this frame to want a definitive answer about the effectiveness of DDDM for ELD which will not be found in this research alone. The authoritative nature of the leaders in the structural frame also affected some of the parameters around the development of this study. Employees (or educators) in the structural frame tend to feel like drones with specializations but are manipulated and controlled by the hierarchy of leadership (Bolman & Deal, 2017). Due to the dynamic created within the structural frame between leaders and teams, the sample of ELD teachers in this study might have felt uncomfortable self-reflecting on the data collection and analyzation being actualized in their daily practice.

The political frame could have also affected the findings of this research due to the differing values and beliefs of the coalition members from the parents, unions, educators, school boards, LEAs, and SEAs. Federal resources fund ESSA (Carney, 2020), and different coalition members frequently have differing ideas on how funds should be allocated (Bolman & Deal, 2017). This study explored the connection between data practices, which require funds, through the pretense of time. This study explored the self-reflection of how educators are using their working time to collect, analyze, and report on instructional data. Most decisions in LEAs come from bargaining and negotiating (Bolman & Deal, 2017), and at this time, the political system governing the ESSA requires minimal data to ensure compliance with ELD (Wiseman & Bell, 2021). Many teachers, including the ELD educators in this study, rely on a teachers' union to advocate for their teachers' rights and provisions. The data investigated in this study was not required by ESSA, SEAs, or most LEAs, nor has been required in the past (Garver, 2022; Wiseman & Bell, 2021). These likely influenced how ELD educators view the importance of the data being explored in this research and their responses in the self-reflected survey.

Conclusion

The present study explored the enacted ELD practices around quality data being collected and analyzed to influence the action of policy and instruction. Literature and anecdotal observations by the research support gaps in data affecting students, teachers, parents, school leaders, and policymakers alike (Wiseman & Bell, 2021; Fowler & Brown, 2018). The current data collection dilemma faced by teachers of ELL will likely find validation for their experiences in the findings of the present research. By developing a deeper understanding of USED and SEA organizations and Title III programming, the researcher was highly focused on exploring how the structural and political frames the current practices of documenting and analyzing student servicing data in Title III and ELD programs.

By considering the organizational frames of USED and SEA as they relate to Title III and ELD, organizational assumptions can be unpacked and used to guide the present research. Data has a significant impact on the USED, SEAs, and LEAs. However, assumptively, state-administered ELD programs, even Title III, had insufficient data collection methods, policies, and data disaggregation for the subgroup of ELLs (Fowler & Brown, 2018; Wiseman & Bell, 2021; Williams, 2020). More surprisingly, the USED had not required SEA and LEA ELD data, reformed data collection and reporting practices in Title III, or even examined the Title III program for accountability since 2010 (Boyle et al., 2010). Consequently, the SEAs report scarce Title III servicing data to the USED (Boyle et al., 2010), furthering the concern about ELD data practices.

SECTION THREE

LITERATURE REVIEW

This literature review examines peer-reviewed research on the current data collection and analyzation practices of educators working in the Every Student Succeeds Act (ESSA) Title III program. This literature review includes research studies on federal provisions for ELLs, including ESSA, Title III, Office of English Language Acquisition (OELA), ELD policies, WIDA standards, current practices and methods in data collection and analyzation, data warehousing, teacher logs, and data reporting. This chapter includes the following sections:

- Federal Provisions for ELLs
- Conceptual Framework
    - Data-driven Decision Making (DDDM)

The following were some of the primary databases used to examine the existing literature regarding ELD monitoring through data collection and analyzation to inform teachers' data-driven decision making: Sage Publication, Eric, ProQuest, Education Research Complete, Gale, and Google Scholar. Keywords used during this search included: ESSA, Title III accountability, ELD programs, data efficacy, Data Wise, data-driven decision making (DDDM), data analysis, data collection, data reporting, ESOL data, equity, technology integration, information and communication technology, teacher log, data warehousing, and WIDA.

This literature review explored the research on federal provisions for ELD programs, data collection and analyzation practices in ELD programs, and the importance of data for instructional decision-making. First, the history and instructional practices in ELD programs were examined to provide knowledge of what occurs during ELD additive instructional services and best practices for language acquisition supported by the WIDA consortium. Then, a synthesis was performed of the varied and vast research connecting to elements of the theoretical framework, DDDM.

Federal Provisions for ELD Programs

Federal provisions for ELLs originated through the Equal Educational Opportunity Act (EEOA) and Bilingual Education Act (BEA), but today much of the SEA and LEA accountability fall back on the compliance with ESSA (Garver, 2022). The lack of research on ELD accountability and the age of the limited existing research are causes for concern; aside from federal funding records and English language proficiency (ELP) achievement scores, minimal data exists regarding ELD accountability (Williams, 2020).

ESSA

Compared to the other subgroups, ELLs are an extremely linguistically and culturally diverse population of students (Birman, & Tran, 2017; Hammond, & Jackson, 2015; UnidosUS, 2018b). English language development (ELD), previously English as a second language (ESL), provisions date back to 1994 (Boyle et al., 2010), and according to the most updated data by the Office of English Language Acquisition (OELA) (2021a), in 2019, 5.1 million ELLs were identified that were located disproportionately across the United States (NCES, 2022). Under NCLB, Title III was solely responsible for ELD provisions, but under ESSA, accountability for all students, including ELLs, is found within the subset, Title I (Villegas & Pompa, 2020).

ESSA: Title III is responsible for ELD specific funding. In 2018, 96.4% of ELLs received Title III funded services through Language Instruction Educational Programs. Most EL populations were found in the Southwest states, and nearly 75% of ELLs spoke Spanish as their primary first language (OELA, 2020b). ELD program models under ESSA compliance are concerned with English proficiency, content-language support, reclassification rate after English proficiency is obtained, and graduation rate (OELA, 2020a), such as WestEd's Quality Teaching for English Learners initiative (Chu & Fong, 2015).

LEAs must use Title III funds to supplement ELD programs, which are designed to assist ELLs' achievement goals, such as implementing EL instructional programs and providing curriculum, and professional development for EL educators in effective language acquisition strategies to prepare ELLs for mainstream and promoting family and community engagement and participation (OELA, 2020a; Boyle et al., 2010; Carney, 2020). Based on ESSA, ELD accountability data from all 50 United States, SEAs and LEAs share the responsibility for establishing Annual Measurable Achievement Objectives (AMAOs) and Adequate Yearly Progress (AYP) to improve the education of ELLs (Garver, 2022; Skinner, 2019). SEA identified goals and monitoring objectives were based on academic achievement, student growth, graduation rates, English language proficiency, and school quality or student success (Portz & Beauchamp, 2022).

SEAs developed unique ESSA plans and goals, but individual states varied greatly on performance goals, including academic achievement definitions and setting performance goals (Portz & Beauchamp, 2022; Boyle et al., 2010; UnidosUS, 2018b). For example, "states used a variety of approaches for determining whether ELs were making progress in learning English… and attaining English proficiency" (Boyle et al., 2010, p. 10). SEAs, LEAs, and schools are held accountable for increasing EL students' ELP and core academic content knowledge (Garver, 2022; Skinner, 2019).

The non-uniformity of ELP definitions and goals complicates the task for federal ELL subgroup provisions and regulations (UnidosUS, 2018b). Most states measure proficiency based on a single annual proficiency assessment operationalized by WIDA, but the proficiency cutscores are not equivalent across states (UnidosUS, 2018b). Additionally, the timelines for proficiency achievement are greatly divided, but most states require proficiency between 5-6 years while four states do not specify a timeline for achieving ELP. ELP progress is a binary indicator, combining ELP achievement and ELP growth (UnidosUS, 2018a), but both components of the indicators are historically based on a single performance data set (UnidosUS, 2018b). The variety of ELD accountability approaches across the United States creates a challenging condition for ELD program synergy.

Nonetheless, in 2021, Title III funds in New Hampshire were distributed based on the number of EL students in the LEA at the per-pupil allocation rate of $180.94 (NHED, 2021). Of the ELL federal funding records available, no Title III funding increase was evident since 2014 (Williams, 2020). Williams (2020) determined that approximately 3.77 million ELLs were educated in the United States in 2002 and Title III funding totaled $664 million. In 2021, 4.9 million ELLs were enrolled in the United States' schools (Mitchell, 2021); however, despite inflation, the per-pupil allotment has not increased in over a decade (Williams, 2020). In fact, Title III funding has stayed the same since 2014: $737,400,000 (Williams, 2020). Between 2002 and 2014, funding increased by 11%, however, during the next five years funding was decreased (Williams, 2020). Consequently, while funding had not changed substantially when considering inflation and the increase in ELLs, funding was insufficient during this period of time (Williams, 2020).

LEAs must provide an individualized ESSA plan for how they plan to use these federal funds (OLEA, 2020a). However, most LEA individualized plans are either incomplete and lacking in detail (Boyle et al., 2010) or exhibit overly ambitious ELP goals (UnidosUS, 2018b). ESSA plans often include anticipated scheduled hours for students (NHED, 2019b), but not the critical evidence that these services occurred and the degree to which the instruction individualized the students' learning opportunities (Leone, 2022). According to the English language acquisition state grant report (2019), LEAs receiving federal funding "must support activities that increase English proficiency and academic achievement of ELs by providing effective language instruction educational programs, supplemental activities, and professional development for teachers and school leaders relating to ELs" (NHED, 2019b, p. 1). Funding is contingent on compliance, and compliance is challenging to achieve due to unclear guidelines, mixed messages, and these varying degrees of ELD AMAOs and accountability standards (Boyle et al., 2010).

School administrators usually assume the responsibility of collecting, analyzing, and reporting data in meaningful ways, but the tools and systems in place render the task nearly impossible for success (Duhigg, 2016). According to the Bureau of Federal Compliance (Carney, 2020), the superintendent must sign the fiscal year program assurances for all ESSA programs in the LEA. By signing, each superintendent is attesting that students, teachers, and program beneficiaries receive equitable access to funds and is verifying the pursuit of the requirements listed in Appendix E (Boyle et al., 2010). Audits are conducted on some of the program components to verify compliance with these assurances, and if discrepancies are found, districts are required to pay back funds (Boyle et al., 2010; NHED, 2019b). Reporting on additive instructional servicing data is an example of a non-auditable task but verified ESOL eligibility would be audited. Unfortunately, during the 2007-2008 school year, only 11 states met the AMAOs specified in their application to receive funding because of the lack of measurement consistency of AMAO scales demonstrated. Significant discrepancies ranged from 0.5%- 70%, and one-fourth of States have missed their AMAOs for 2-4 consecutive years (Boyle et al., 2010).

ESSA provisions and funding were supplied to local educational agencies (LEAs) for the purpose of enhancing the quality of English language development (ELD) programs for English language learners (ELLs) (UnidosUS, 2018b). However, educating this population is no simple endeavor as ELLs tend to vary greatly in their educational, linguistic, social, and emotional needs (Estrada et al., 2020; Williams, 2020; Wiseman & Bell, 2021). As of this research, instructional models of ELD (push-in, pullout, co-teaching, and bilingual) and daily instructional curriculum, practices, and strategies fluctuate considerably (Holfester, 2021).

Nationally, ELD programs are laden with complexities and ambiguities (Garver, 2022), making ELD data standards beyond the ELP assessments vital to better understand these programs and the ELLs being serviced (Fernando, 2020; Wiseman & Bell, 2021). Some states, specifically those states with the greatest population of ELL, have developed their own proficiency assessments. New York State Education Department (2022) developed the New York State English as a Second Language Achievement Test (NYSESLAT), and the California Department of Education (2022) designed the English Language Proficiency Assessments for California (ELPAC). However, these states are outliers, as an organization, commonly known as WIDA, has emerged to guide ELD programs across the majority of the country in ELP achievement.

WIDA Consortium. Schools in 41 states across the United States are a part of the World-Class Instructional Design and Assessment (WIDA) consortium, using high-quality standards and instruction to support and assess ELLs (UnidosUS, 2018b; WIDA, 2022). The consortium is dedicated to advancing academic language development to promote student achievement for culturally and linguistically diverse students (WIDA, 2022). The consortium has developed five standards for instruction. The five standards include communication for social and instructional purposes, information, ideas, and concepts for language arts, mathematics, science, and social studies (WIDA, 2022). The WIDA standards format nestles the proficiency level descriptors, language expectations, and language uses for each standard (WIDA, 2022).

In 2016, the yearly, nationally accepted WIDA ACCESS language proficiency assessment was operationalized (UnidosUS, 2018b), and as of 2022, it is the most widely accepted and used form of data collection and reporting for Title III (WIDA, 2022). States have used the scores from the WIDA ACCESS achievement assessment to assign students an ELP score (UnidosUS, 2018b) and track students' ELD over time. Inopportunely, states ELP definitions are inconsistent and not clearly identified in the individual state's ESSA plans (UnidosUS, 2018b), causing complications in ELD data practice. Further, the debate on if meaningful and accurate assessment data of ELP and achievement can be collected through the existing instruments should be considered (Fairbairn & Fox, 2009).

Current Data Practices in ELD

A single standardized assessment does not provide enough metrics to demonstrate progress monitoring or equitable accountability to this underserved population (Fowler & Brown, 2018; Wiseman & Bell, 2021; Fairbairn & Fox, 2009). As such, the question becomes; what is the most effective way to standardize the documentation of the instructional services received by the complex, growing subgroup of ELLs? For many decades, traditional data collection methods have been used to document student services (Ruf, 2012). The most common form of traditional data collection is paper and pencil methods, such as records of schedules, attendance, and even servicing notes (Ruf, 2012). Some educators keep very minimal evidence of documentation and ELD service monitoring (Wiseman & Bell, 2021). In the cases where an educator might have kept detailed paper records, imagine the bookshelves filled with binders full of pages of notes of servicing data. Furthermore, creating reports would be incredibly challenging even with the most organized system if a district were audited for funding compliance or an administrator needed information on a student's total servicing time.

Achievement data is worrisome across the field of education, especially so for culturally and linguistically diverse students (Fowler & Brown, 2018). Furthermore, according to Wiseman and Bell (2021), educational data for ELLs is usually "anecdotal, limited in scope, or related to population size rather than disaggregate-able experiences" (p. 2). Furthermore, language data is the only educational data available on ELD programs and ELLs (Wiseman & Bell, 2021). The lack of empirical, publicly available, systematically collected, disaggregated data makes it impossible to conduct cross-national analyses limiting the ability of policymakers when attempting to make equitable, data driven decisions (Wiseman & Bell, 2021). Accountability structures tangibly increase student scores (Fowler & Brown, 2018). However, the specific academic needs of this subgroup have never been identified due to the lack of data (Wiseman & Bell, 2021).

Heiskanen et al. (2019) researched how educators created and used sequential pedagogical documents for children with special educational needs. The findings demonstrated that patterns of student support documentation were missing, repetitious, disorganized, and explicit (Heiskanen et al., 2019). Only 13% (n = 257) of the documents examined were explicit examples where "support was evaluated and developed systematically" (Heiskanen et al., 2019, p. 333). The researchers found that 87% of support records were lacking, imprecise, vague, incoherent, or nonexistent, which made it impossible to interpret the student data correctly or trust the analytics determined from the data calculations using these records.

Teaching English to Speakers of Other Languages (TESOL) International Association is a professional community acknowledged worldwide for the ELD learning opportunities, research, standards, and advocacy. The TESOL organization was founded in 1966 and today, is known for best practices in the field of ELD. The TESOL Principles of Exemplary Teaching of English Learners, includes both knowledge of students (TESOL, 2023a) and monitoring and assessing ELP growth (TESOL, 2023b). These standards are encouraged to "provide teachers with the knowledge to make informed decisions to improve instruction" (TESOL, 2023c, pp. 7). *Principle One: Know Your Learners* encouraged educators to obtain data on ELLs linguistic and academic backgrounds (TESOL, 2023a) and *Principle Five: Monitor and Assess Student Language Development* suggested teacher record keeping to monitoring errors, formative assessment, and a collaborative approach to the shared responsibility of educating ELLs called School-wide English Learning (SWEL) (TESOL, 2023b). These principles are best practices for the ELD field, but the enactment of these standards were minimal in the ELD literature on data usage.

A thorough examination of existing research revealed no solution for ELD educators to adequately document, analyze, and report the instruction provided to ELLs in additive instructional services (Boyle et al., 2010; Carney, 2020; Wiseman & Bell, 2021). Data has proven to be a valuable tool for influencing quality decision-making (Boudett et al., 2015; Ikemoto & Marsh, 2007; Mandinach, 2006; Scaaf, 2015) and TESOL International Association identified monitoring and assessing student language develop as one of their six principles of exemplary ELD teaching (TESOL, 2023c). Unfortunately, as of 2023, data collection rarely occurs in ELD, and where it does occur, the data lacks explicitness and overall coherence across the field (Boyle et al., 2010; Wiseman & Bell, 2021; Fowler & Brown, 2018). For this reason, an empirical rationale for the present study existed, as this study examined the enacted ELD data collection and analyzation in New Hampshire public ELD programs.

Theoretical Framework

The present study offers essential findings regarding the current educational data practices enacted by ELD educators in the New Hampshire public school programs and the perceived importance of data practices to provide accurate, higher quality, and provide meaningful instructional experiences in ELD settings. Educational data is the crucial currency for this study of data collection and analyzation in ELD to drive instructional decision-making, supporting the rationale of this study as a meaningful addition to academic research. Though power has the potential to be used negatively if focused on deficiency, there is power in data and information and the way it is used (Shaked, 2010). The data-driven decision-making (DDDM) framework demonstrates the intersectionality between data, information, and knowledge (Mandinach et al., 2006) and the connection to the research criterion; data collection and analyzation. While no literature was located on Title III educator data practices, the following section will describe the key research findings on the three components of the DDDM framework and emphasize how each supports and scaffolds the present study.

Data-driven Decision Making (DDDM)

Data-driven decision-making (DDDM) is a well-known term for data collection and use, though the practice has many subsets, such as Data-Informed Decision Making (Ikemoto & Marsh, 2007; Mandinach et al., 2015; Young et al., 2018), Data-Based Decision Making (Gesel et al., 2021; Mandinach & Schildkamp, 2021b; Visscher, 2021) and Wise Data-Driven Decision Making (WD3M) (Namvar & Intezari, 2021). DDDM and the alternative frameworks emphasize the need for balance between empirical data and formative data, and the leading role of the interpretive action derived from the data supply (Mandinach & Schildkamp, 2021a). Young et al. (2018) called data the raw material that gleans meaning when used well and acknowledged the arsenal of data types, the distinctive purposes of the individual data types, and their analyzations in the educational system. For the purposes of this proposal, DDDM is the acronym that will be used for the all-encompassing framework of data used to guide instructional purposes.

DDDM is defined as the use of students' performance data to inform educational decisions (Buzhardt et al., 2020; Mandinach, 2012). According to Buzhardt et al. (2020), DDDM is an essential component of a multi-tiered system of support (MTSS) approach, which is driven "from formative progress-monitoring measures of students' growth in the school curriculum" (p. 75). Teachers collected, analyzed, and used data to inform their decisions regarding students' qualifications for additional support in the Response to Intervention (RTI) model (RTI Action Network, 2022). Unfortunately, student performance data often served as the only valued indicator in educators' instructional decision-making (Wiseman & Bell, 2021). Fernando (2020) echoed the importance of meaningful data-informing insight, which drives decisions and enhances learning. Henig (2012) described data-driven decision-making as a political, ideological, and technical data regime. In comparison, Evans (2015) explained, "the phenomena of DDDM [as] a summation of policies, values, and tools that shape educators' engagement with data" (p. 7). Mandinach and Schildkamp (2021a) described how data use is complex and imperative and "requires the use of multiple sources of qualitative, as well as quantitative data, and not solely achievement data" (p. 1). The researchers presented a clear process of setting goals, identifying data, and collecting data to be analyzed and interpreted to improve educational experiences (Mandinach & Schildkamp, 2021a).

Gesel et al. (2021) reiterated the importance of using data to make decisions, specifically under the data-based decision-making frame (DBDM), by analyzing 26 studies with 1,193 teacher participants. The meta-analysis by Gesel et al. verified DBDM as a contributor to student achievement, especially when teachers were exposed to DBDM professional development and used the entire DBDM process with fidelity. DBDM was used as a data system to align instructional decisions and interventions and to monitor student progress (Gesel et al., 2021). Using the DBDM process, teachers' data collection practices were more consistent and reliable, and teachers made more confident instructional and intervention decisions, which produced better student outcomes (Gesel et al., 2021), and even lessened the achievement gap (Fuch et al., 2015). Without the knowledge and efficacy in DBDM, Stecker et al. (2005) found that teachers were frustrated, struggling, challenged, lacked time and strategy for data use, and were reluctant to collect data. Data-based individualization is a subsequent model of DBDM, which includes the following components: intervention program foundation, progress monitoring, diagnostic assessment of areas of student weaknesses, and an intensified or specialized intervention based on the data (Gesel et al., 2021, p. 270).

Another well-known example of DDDM is Harvard School of Education's Data Wise, a process of incorporating data into our educational decision-making through an eight-step activity designed to help school leaders engage with student data more effectively (Boudett et al., 2015). The eight actionable steps fall into three categories; Prepare, Inquire, and Act. "Initially, schools prepare- they engage in activities that establish a foundation for learning from student assessment results. They then inquire, and subsequently, they act on what they learned. They then cycle back to further inquiry" (Boudett et al., 2015, p. 5). Boudett (2015) described Data Wise as a process to organize and bring coherence to the use of data to improve education, rather than a program to be implemented. The foundation of Data Wise is the ACE Habits of the Mind, "Shared commitment to *Action*, assessment, and adjustment. Intentional *Collaboration***.** Relentless focus on *Evidence*" (Boudett et al., 2015, p. 7). Multiple evidence-based DDDM systems exist, but Data Wise is relatively well-known and widely used.

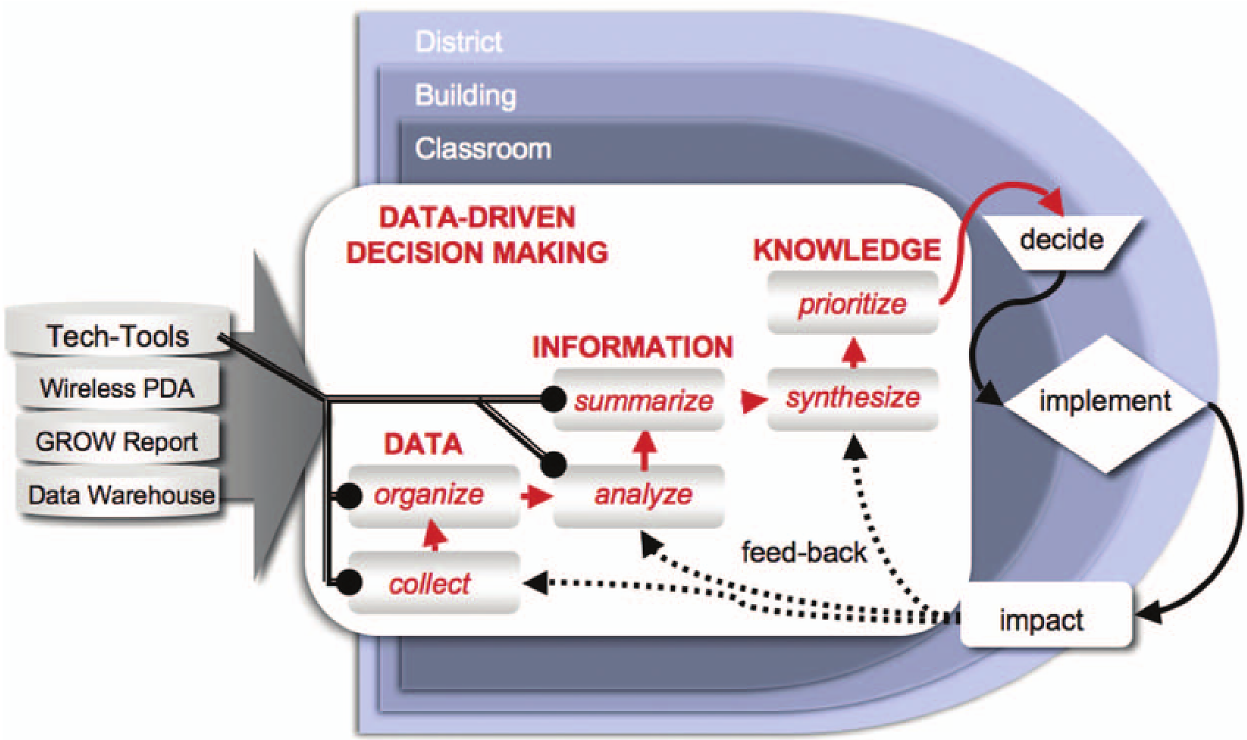
Similarly, wise data-driven decision-making (WD3M) combines the need for quality data and the psychological ability to apply the data to action (Namvar & Intezari, 2021). Namvar and Intezari (2021) found that "despite analytics being one of the essential elements of the modern decision-support system, in most organizations, analytics [are] loosely coupled with decision-making and much less with wise decision-making" (p. 109). The researchers developed W3DM by studying how managers in corporations use analytics to make wiser decisions. The W3DM framework follows the pathway; report generation, trustworthiness analysis, appropriateness analysis, and alternative selection (Namvar & Intezari, 2021).

The W3DM framework is similar to the DDDM framework by Mandinach et al. (2006), but it adds an emotional-cognitive element, wisdom. Namvar and Intezari (2021) divided wisdom into two categories: rational and nonrational. Rational wisdom is how an individual uses analytics to make a decision. Nonrational wisdom is the judgment and human insight side of decision-making. Though the DDDM frame is the chosen framework for this study, wisdom as described by Namvar and Intezari, is not absent from the DDDM, but rather, encompassed and embedded in each component of the DDDM framework. For example, DDDM data should not be used if it is not analyzed and confirmed trustworthy. So, while the W3DM adds a perceived newness to DDDM, the *wisdom* of assessing for trustworthiness, choosing appropriate analysis, and deciding when to make an alternative selection of data is inherently already a component of DDDM, even without explicitly being highlighted by the framework.

Data-driven Decision Making Framework. Mandinach et al. (2006) developed the DDDM framework with the influence of many contributors, including Ackoff (1989), Drucker (1989), and Light et al. (2004). Ackoff (1989) explained, “Data, information, and knowledge form a continuum in which data [is] transformed to information, and ultimately to knowledge that can be applied to make decisions” (as cited by Mandinach et al., 2006). When viewing the conceptual framework of DDDM in Figure 3, proceeding from left to right is the flow of data for all levels of educational organizations: district, building, and classroom.

Figure 3

Data-driven Decision-Making Framework



(Mandinach et al., 2006, p. 7)

According to the framework, data comes from many modes, methods, and sources (Mandinach et al., 2006), depicted on the left of Figure 3. The *data* enters in a raw, unaltered form, and this stage of the framework is the collection and organization of the data without any attached meaning (Mandinach et al., 2006). The next component, *information*, is where the data is given meaning within a context (Mandinach et al., 2006). Mandinach et al. (2006) stated that when data and information combine, the result can be "used to comprehend and organize our environment, unveiling an understanding of relations between data and context" (p. 7). Lastly, *knowledge* is where the data gets used for instructional planning and future implications. This component determines which data to analyze, which data is perceived as useful, and which data to prioritize in instructional decision-making (Mandinach et al., 2006). After the information progresses through these three components, decisions are made, implemented, and then assessed for impact, which leads to the feedback loop with further information to use in the subsequent DDDM processes.

DDDM is an effective framework with considerable research support (Mandinach et al., 2006; Fry, 2017; Schaaf, 2015, Usher et al., 2021). Fry (2017) explored how 24 school administrators perceived and used DDDM in nine districts in Pennsylvania. Data was collected through semi-structured interviews, with the researcher focusing on the process and perceptions of DDDM as a true grounded theory. Through individual interviews and monthly meetings, Fry reported that using state-mandated achievement data as a baseline, successful utilization of DDDM occurred and guided specific school processes to support student achievement.

Using the DDDM process, multiple participants described a culture of continuous growth focused on student learning compared to a culture of compliance regarding student learning (Fry, 2017). Fry (2017) also identified that participants were utilizing a DDDM model to support planning for the whole child and beyond the areas of student achievement, school culture, and safety. While DDDM was an effective tool to support school leaders, serve their schools, and guide desirable achievement growth and specific education goals, school leadership is a necessary advocate of the training, support, and process of DDDM (Fry, 2017).

Data. The first element of DDDM, *data,* is considered the most valuable and intangible asset in all sectors (Fernando, 2020). Educational data can fall into many categories, but achievement data is the most universal measure when considering data influencing educational policy and decisions (Dodman et al., 2021; Portz & Beauchamp, 2022). Fowler and Brown (2018) described the intended purpose and use of data:

> The purpose of collecting, disaggregating, and consuming data is to better improve teaching and learning practices for students. This cannot be done in a way that does not take into account the learning needs of students, which is why data should begin to inform the conversations around equitable outcomes for students based on the student's relationship with the teacher, the educational system, and their learning processes. (p. 24)

Furthermore, Shaked (2010) emphasized the power of strength-based data metrics and performance measurements toward setting and keeping strategic goals, stating, "what gets measured gets noticed" (p. 51). Shaked recommended in-depth conversations about the data collected and its wholeness as what is focused on grows. Metrics help bring necessary but lacking data about the problem of practice in the educational system. Shaked's strength-based approach ensures the right questions are being asked, such as

- What do the metric data collected demonstrate?
- How do the metrics get used to achieve progress toward the current version of the desired future?
- How do we know that the goals were achieved?
- How do we know that we have made progress towards the goals?

(Shaked, 2010, p. 54) Data can be especially useful when asking the *right* questions, but not all data is equally recognized or can be used in the same ways.

Data variety makes the perceptual landscape lush. According to Fitzpatrick and Margolin (2004), data usually falls into 4 categories: achievement data, demographic data, program data, and perceptual data. While the Minnesota Department of Education (2016) reported similar data types, the organization included a fifth data category: fidelity of implementation data. The following section will devolve into the presence of each type of data in ELD.

- Achievement data. Achievement data includes large-scale state and local assessments providing results disaggregated to provide demographic data, achievement trends, and standard achievement (MED, 2016). Analytics and results from achievement assessments are the most widely accessible (Portz & Beauchamp, 2022; Fitzpatrick & Margolin, 2004), and often one of the only types of data available for all students, including students learning English as a second language (Fowler & Brown, 2018). This data is considered accountability data and the primary audience is policymakers, community, administrators, and teachers.
- Demographic data. Similar in scope and audience, demographic data is merely the snapshot of a student's ethnicity, family income status, language, enrollment patterns, and behavior and social attributes of students. District and school-level teams analyzing the demographic data determine the trends of the student population and the factors inside and outside of school that may help understand students better.
- Program data. Program data provides information about the quality and effectiveness of programs (MED, 2016). Program data is often considered action research and not always easily quantifiable. The primary focus of program data is exploring the success and

efficacy of programs in "bringing about the academic excellence articulated in our standards" (MED, 2016, p. 5).

- Perceptual data. The opinions and perceptions of the school community, students, or guardians. For students, this is often considered self-reflection. Areas where perceptual data is the most useful are measuring "…academic standards, school leadership, quality of instruction, and school climate" (Fitzpatrick & Margolin, 2004, p. 3).
- Fidelity of implementation data. The fidelity of implementation data "measures adult behavior and the extent to which critical components of a strategy or system are implemented" (MED, 2016). Common data types available are walk-thru data or observational or coaching notes (MED, 2016).

Data variety is essential to the process of turning data into useful knowledge (Finn, 2022). Unfortunately, the only broadly recognized and required documented data used nationally for ELLs are achievement test scores through the yearly English language proficiency assessment (Fowler & Brown, 2018). Without data and metrics available, Shaked's (2010) process of asking questions to guide data-informed decisions cannot occur. The following section will explore research on various instructional data collection practices.

Data Collection. In reference to the DDDM framework, *data* combines how educational data is collected and organized. As described previously, school administrators receiving ESSA funds often face great scrutiny to demonstrate compliance and learning for all students (Skinner, 2019). Ruf (2012) identified the quality of students' outcomes and systematic progress monitoring as primary objectives for data collection. For example, curriculum-based measurement was one way to demonstrate such progress and design better instructional programs for enhanced student achievement. Sandall et al. (2004) "described the three major reasons for monitoring students' performance through data collection: (a) to validate initial assessment information, (b) to develop a record of progress over time, and (c) to evaluate instructional effectiveness and make instructional decisions" (as cited by Ruf, 2012, p. 18).

Mngomezulu et al. (2022) explored the struggles teachers experienced when using ongoing formative assessment to "identify learner needs and make appropriate adjustments to teaching and learning" (p. 158). Formative assessments are an evidence-based pedagogical tool with many researched strategies for data use (Mngomezulu et al., 2022). However, teachers still reported an increase in administrative workload with the data collection, as well as difficulty using formative assessment, which in turn created a feeling of incompetence. Assessment is often narrowed to summative evaluations for grades, or high-stakes student achievement tests, both of which do not offer a full vantage point of student ability, especially for disadvantaged or marginalized students (Mngomezulu et al., 2022). Conversely, Mngomezulu et al. described the purpose of formative assessment to better "…facilitate learning and provision of information to enable learners to be more effective and close the existing gap in their learning" (p. 160). One way Mngomezulu et al. found to lessen teachers' aversion to formative assessment was through professional development to become more confident and competent in using collecting data through formative assessment strategies and then analyzing the data to scaffold student learning.

Ruf (2012) examined the barriers to data collection through the progress monitoring practices in special education settings, such as the nature of the setting, data management, time, and the nature of the IEPs. While some of the barriers with IEPs do not pertain to Title III and ELD, other barriers identified are the same in both categories. Ruf found that one barrier teachers faced was the lack of data necessary to make informed decisions about their students and that data collection adversely affected the flow of their classroom routines. The ways in which teachers incorporated the data in their interventions and physically collected the data were critical factors of data collection frequently missed when solely utilizing standardized assessment data. Ruf also identified the time barriers for teachers and the shortage of personnel with training as important components of data collection and analysis research.

Teacher data logs as a form of data collection were first documented in the 1980s as a component of Michigan State university's beginning teacher program (Rowen & Correnti, 2009). Teacher logs involved the frequent and routine self-reflective documentation of instructional services and decisions (Rowen et al., 2004). Rowen et al. (2004) demonstrated the power of teacher data logs to measure enacted curriculum data rather than the intended curriculum with great measurement accuracy. Unlike other types of classroom or instructional measurement approaches, teacher data logs collect very specific aspects of the teacher's practice. For examples of how teacher logs compare to other types of classroom measurement approaches, see Table 2.

Table 2

Rowen's Classroom Data Measurement Tools

Tools	About	Advantages	Disadvantages
Annual (or Biannual) Teacher Survey	• Annual or biannual • Teacher self-report on their own behavior • Broad range of questions	• Common nationally & internationally • Minimally expensive • Frequently used for large-sample data collection • Measure content coverage & pedagogy • Reliable and valid for broad measures of instruction	• Limited ability to measure all classroom practices • No measurement of social interactions • Lack measurement of quality & complexities • Many errors due teacher self-report reliability & influence of socially desirable responses • Terminology created errors and response confusion • Estimation & retrospective reporting can increase errors
Classroom Observation	• Completed by the trained observer • Data collected on notes or video • Coded and analyzed later	• Flexible • Face validity • Highly respected by researchers & in the field of education as a gold-standard data collect practice & to assess fidelity of an implementation	• Expensive (personnel, travel expensive, training, video, & audio equipment) • Trained observers necessary • On-going training & skill development for trainers • Limited use in large-scale sample & types of interactions captured • High variability in field of education challenges the approaches generalizability • Possible inconsistency amongst observers & subjectivity
Teacher Log	• Teachers' self-report on instructional practices on a defined basis • Include paper/pencil or electronic methods • Measure very specific aspects of teacher practice • Frequently administered	• Cost-effective • Better self-reporting due to frequency & quality of submissions -Increased generalizability • Highly reliable & valid	• Ineffective for measuring social interactions &classroom organization • Can result in errors due teacher self-report reliability & influence of socially desirable responses (combated by frequency) • Increased respondent burden • Respondent system training necessary

(Developed based on Rowen & Correnti, 2009)

Rowen and Correnti (2009) found that self-estimation in retrospect, commonly used in annual or biannual teacher surveys, was especially inaccurate in behaviors that rarely occurred and that frequently occurred. Teacher logs, implemented correctly and combined with user training, collected valid, reliable, and inexpensive data on classroom practices (Rowen & Correnti, 2009). In their earlier work, Rowen et al. (2004) addressed the fact that students will learn innately, which is why it is increasingly important to document and determine what makes learning the most powerful and effective. For example, Nelson (2003) found that ELLs acquired English at a significantly greater pace and confidence when instructed on syntax (55% increase) and semantics (49% increase), as opposed to limited to no English instruction (12% increase). Failure to collect instructional data in additive instructional services risks the powerful realization that teachers' instruction matters.

Technology has become increasingly important for teachers and students due to globalization and COVID-19 (Adams, 2021; Mahalis, 2021; Robinson, 2021), which has influenced how data is collected. According to the Federal Results Driven Accountability mandate (2004), special education educators are often required to use electronic documentation for accountability, and several software platforms have surfaced to meet the need for data collecting and reporting (Kurz et al., 2010), such as myiLOGS (Kurz et al., 2010), MaxCapture (Sivic Solutions Group, 2022), and DOKed (Leone, 2021). MyiLOGS is a teacher logging tool for documenting the three components of Opportunity to Learn (OTL); time, context, and quality (Kurz, 2010). The Frontline Education and MaxCapture are electronic management systems designed for use in special education programs and Medicaid tracking and billing. Both data warehouses are focused on operations and compliance by providing modular software products and services to the k-12 education market in the United States. The intended customers are school administrators "who are looking for a platform of connected solutions to help attract, support and retain great educators, automatizing workflows, gathering data, and crossing departmental silos" (Frontline Education Acquires Accelify Solutions, 2019, p. 1). DOKed is a new software platform in development to document enacted ESOL servicing data, such as attendance, instructional method, duration, and lesson notes (Leone, 2021).

Some teachers have used Google Suites for teaching and recording student data (Adams, 2021; Albashtawi & Bataineh, 2020; Mahalis, 2021; Robinson, 2021; Yen & Mohamad, 2021). Agustina and Purnawarman (2020) determined that as widespread as Google Suites may be, teachers and students lacked satisfaction with the effectiveness of the Google tools for formative assessment. Assessment data and servicing data are similar in many ways, and a lack of satisfaction was expressed with using Google Suites as a resource for large-scale data collection and feedback or reports (Agustina & Purnawarman, 2020). Special Education and TESOL require documentation for compliance, though the necessary degree and depth vary greatly not yet offered on the Google Suites platform (Agustina & Purnawarman, 2020).

Due to the limited pool of research on data collection for educational purposes, Ruf (2012) compared the need for technological data support and integration in the classroom with mobile electronic data collection in the healthcare field. Ruf observed that data collection using non-electronic strategies was inaccurate and contained errors in two-thirds of the studies. Electronic data collection was the preferred data entry method and enhanced communication between educators and specialists, which promoted positive effects for students and educators (Ruf, 2012). Ruf demonstrated the high value of handheld technology for collecting sensitive data and user satisfaction by improving documentation, reducing medical errors, and improving decision support. The healthcare field relies on efficient and effective data collection and implementations, specifically by mobile electronic data collection systems based on speed, ease of use, accuracy, and user satisfaction. Technology is vital to the healthcare field for real-time documentation, facilitating data integrity and availability, making the healthcare field a forerunner for quality data collection, and a wise partnered research field with special education or TESOL programs.

According to Dale and Hagen (2007), traditional paper-based approaches did not match the performance of personal digital assistants (PDAs) as a collection tool “in terms of feasibility, protocol compliance, data accuracy, and subject acceptability” (Ruf, 2012, p. 23). Specifically, Childs et al. (n.d.) found that electronic data collection was 36% faster using a PDA than traditional paper-based methods. Tarbox et al. (2010) determined the contrary, stating that it even took instructional time from student sessions. Tarbox et al. also stated that the reporting, mainly graphs, produced using electronically collected data was significantly faster to create. Ruf (2012) acknowledged that teachers had a longstanding comfortability and familiarity with paper-based recording. However, electronic data collection and reporting solutions are necessary for the many reasons examined in this paper and will lead to positive student learning outcomes (Todman & Dugard, 2001).

Ruf determined that teachers described five affordances of PDA technology: multimedia-access tools and connectivity tools, capture tools, representational tools, and analytical tools, which encompass three subcategories: scientific, reflective, and multimedia. Ruf explained:

> Scientific data collection improves users’ knowledge by recording relevant information and providing immediate feedback. Reflective applications allow users to record observations in the working/learning environment that can later be used to aid in reflection. Multimedia data can also provide the basis for reflection. (Ruf, 2012, p. 29)

The differentiations between educational data collection tools are a vital component of developing an effective ELD data collection and reporting practice that is not only electronic, but viable for the purposes (Ruf, 2012).

DBDM software added value to the practice of data collection by offering more comprehensive skill analyses and instructional recommendations (Stecker et al., 2005) and "increas[ing] the efficiency and the acceptability of [data] practices for teachers" (Gesel et al., 2021, p. 270). The research by Fuchs et al. (1989a) and Fuchs et al. (1989b) collected, analyzed, and graphed data electronically through software. The software used by Fuchs et al. (1989a) assisted in the interpretation of the data, which was found to decrease interpretation errors and helped guide data evaluation. Fuchs et al. (1989b) used software that created data-guided goals. Both software updates were imperative because teachers had previously reported struggling to identify the uses of the data derived from the software data reports. Later research by Fuchs et al. (1991a) and Fuch et al. (1991b) used further updated software that reported more explicit instructional recommendations, demonstrating the adaptive process of data software creation and the effectiveness of an intentional and meaningful data collection software.

Data and Information. The educational data is summarized and analyzed when data and information intersect in the DDDM framework. The information begins to make sense in this component (Mandinach et al., 2006). One gauge of how the information is understood and how comfortable educators are with the data and analytics is through data efficacy. On the other end of the spectrum, twenty-first-century technology is becoming more advanced, and, in many scenarios, data warehousing is replacing the human aspect necessary for an individual to make sense of the data at hand.

According to Dunn et al. (2013), DDDM efficacy encompasses "teachers' beliefs about their abilities to successfully engage in classroom level DDDM" (p. 223). When considering self-reflection or belief, literacy and optimism are at one pole, and concern and lack of understanding is at the opposite pole (Dunn et al., 2013). Feelings of concern of innovation include anxiety, "[negative] perceptions, preoccupations, considerations, contentment, and frustration" (Dunn et al., 2013, p. 223), and can be avoided through the implementation of effective professional development. Furthermore, Dunn et al. acknowledged that data efficacy could strongly predict change action. Dunn et al. also demonstrated how teachers' data efficacy beliefs directly determine teachers' concerns about a change since "...concerns are comprised of thoughts and feelings about a target innovation" (p. 224) and "efficacy beliefs affect the way one thinks and feels" (p. 224).

Dunn et al. (2013) described DDDM as a learner-centered practice in which teachers use various data to guide instruction. However, the researchers found that DDDM was often perceived by teachers as novel and stress-inducing (Dunn et al., 2013). Teacher data efficacy can predict academic decision-making since it reveals the effectiveness of enacted instructional practices, guiding "interventions to facilitate students reaching appropriate learning goals" (Dunn et al., 2013, p. 225). Dunn et al. (2013) found that data efficacy comprised three parts; data access and identification, DDDM anxiety, and data tools and technology; and DDDM efficacy impacted concerns about data information processing collaboration and refocusing. Regarding the correlation between DDDM efficacy and DDDM concern, Dunn et al. found that DDDM knowledge and DDDM anxiety significantly influenced DDDM efficacy which greatly impacted teachers' concerns about DDDM. Stress, resilience, and levels of confidence with innovation (statistics, data systems, technology) are some components that affect teacher efficacy (Dunn et al., 2013).

Naturally, data and information involve a very human element in making sense of the data to plan action. Duhigg (2016) found that data was extremely valuable and transformative, and data interpretation was the most vital component of the process. Teachers who engaged with the data were more successful and confident at making sense of the information and applying the information to data-driven actions, as compared to teachers who related to the information passively (Duhigg, 2016). After implementing a cognitive disfluency initiative to better understand and use data, standards achievement at Cincinnati's South Avondale Elementary School rose from 37% to over 80%. Cognitive disfluency is the process of making data slightly more challenging to understand, which triggers a response of being removed from a comfort zone and causes the mind to "process information more carefully, deeply, and abstractly" (Duhigg, 2016, pp. 7). To gain the most from the data, these initial and intentional interpretations of the presented information are crucial before determining further actions (Duhigg, 2016). Data warehousing, mining, and data dashboards are all important for information collection and presentation, but data interpretation often requires individual thought to derive understanding and usefulness (Duhigg, 2016).

Data Warehouses are software databases intended to contain and compile student data, including attendance, performance, assessment scores, and behavior (Mandinach et al, 2006). While data warehouses are an asset to DDDM, Zigmund (2020) described these systems' early interfaces and navigation as "complicated", and difficult to successfully retrieve data. Between the early 2000s to 2020, these software systems evolved for more successful use by educators (Mandinach & Gummer, 2016). To maximize effectiveness, data warehouses compile the data necessary for educators to make sense of the data and make data-driven decisions. Bernhardt (2013) explained that "by intersecting this data in response to identified problems, analysis results in knowledge to form solutions" (as cited by Zigmund, 2020). Many SEAs and LEAs have some form of data warehouse for teachers and administration, for example, PVASS for The Pennsylvania Department of Education, and MaxCapture for New Hampshire special education data. The PVASS interface contained relevant data for schools and LEA, as opposed to the data needed of the teachers (Zigmund, 2020).

In Pennsylvania, data compiled in the data warehouse affected teacher evaluations (Zigmund, 2020). "PVASS identifies that the students' teachers have the instructional responsibility for their performance on state assessments for the content area being assessed. The average of the student outcome data makes up the teacher-specific data area of the teacher's evaluation" (Zigmund, 2020, p. 28). Zigmund found that 29% of educators studied used the PVASS data warehouse interface in their DDDM approach in their classrooms, while only 13% of educators used standardized testing results. Zigmund also found that many types of data were used on varying levels, but by consensus, the data used most was the information teachers could easily access and analyze. Unfortunately, some teachers reported not using data to inform classroom instruction despite the readily available data warehousing software and strategies (Zigmund, 2020).

Through an analysis of 12 studies on data integration in the educational sector, Fernando (2020) determined that data technology implementation is an informational processing solution to obtain better insights and make accurate decisions. Implementation of data involves technologies such as big data, data mining and data analytics, business intelligence, and machine learning (Fernando, 2020). Many industries use data science and technologies, including banking, retail, aviation, insurance, and travel (Fernando, 2020). Fernando (2020) blames costly and lack of technical staff for the slow adoption of data infrastructure in the field of education. Fernando (2020) claimed that the implementation of data technology "would be a benefit to universities, statistical departments, and other government agencies in order to reveal insight and information to make efficient and effective decisions" (p. 2). Educational data warehouses can be utilized to find patterns in large amounts of data by LEAs or SEAs on varying scales. The most beneficial database for data warehousing stores, computerizes, and manipulates large amounts of data to allow for data extraction and interpretation to make better and more accurate decisions (Fernando, 2020). Fernando found evidence of the importance of data warehousing to analyze trends that will affect the future and enhance productivity in schools.

Data and Knowledge. Data and Knowledge intersect in the DDDM framework where the necessary information and skills are applied to the data collected for effective analyzation and use (Mandinach et al., 2006). Engaging with data meaningfully takes practice for effective application (Duhigg, 2016). After collecting the data and being able to understand the implications, teachers knowledgeable in data analytics and outcomes can formulate action plans for instructional decisions and further data collection (Fernando, 2020). Professional development is one of the primary ways that educators acquire new knowledge in their field and specialization. Technological acceptance and efficacy combine the importance of technology used for data warehousing and the knowledge necessary to use electronic data collection effectively. The DDDM framework uses data knowledge to synthesize and prioritize knowledge to design and implement instructional strategies that will impact better data and ultimately student achievement.

Professional learning, commonly known as professional development (PD), is one of the greatest acts of knowledge builders, support for educators, and improvers of educational instruction and services (Kennedy, 2016; Kurz, 2018; Schnellert, 2021; White, 2021). Hall-Mills et al. (2022) found that post-Covid-19 educators clearly articulated their lack of training in telepractice and their desire for PD opportunities specific to their role and responsibility. PD combines the practices derived from change, organizational, and learning theories in guiding employees through transformation, innovation, and challenging times (Kennedy, 2016). The success of PD and its effectiveness in improving teaching practices has been credited to the PD program design, collaborative pressures, and ideas for enactment (Kennedy, 2016). Schnellert (2021) acknowledged the power of learning networks and the extrinsic motivation that is created from communal learning. Hall-Mills et al. found that educators in their focus groups who participated in more PL opportunities were more likely to exhibit the positive impacts of adoption, confidence, and efficacy of the telepractice mode of therapy delivery, as described by the educators themselves.

Data efficacy, a primary component of learning success, is developed over time and through positive, affirming experiences (Bandura, 1997; Dunn et al., 2013). Gesel et al. (2021) found that data efficacy was strongly linked to professional development (PD) regarding the implementation and expectations of teaching procedures, and "[has] a cascading effect on student achievement" (p. 279). Gesel et al. (2021) examined the teacher outcome associated with PD on data knowledge and found a significant effect ($g = 0.57$) through the examined studies in the meta-analysis. The researchers acknowledged the importance of data self-efficacy because teachers' beliefs about their abilities are greatly intertwined with knowledge, skills, and student outcomes (Gesel et al., 2021).

Technological acceptance of data initiatives incorporates information and communication technologies into the future norms of society and education (Fernando, 2020; Kurilovas, 2016). Parr et al. (2004) emphasized the importance of reducing computer anxiety among users before introducing new electronic data solutions and Kurilovas (2016) examined methods of evaluating the suitability, acceptance, and use of IT applications for education. The most accepted solutions included individualized profiles and styles accounted for within the IT technology (Kurilovas, 2016). Technology acceptance can be assessed using multiple measurements, such as the Educational Technology Acceptance & Satisfaction Model (ETAS-M) (Poelmans et al., 2009) and the Unified Theory on Acceptance and Use of Technology (UTAUT) model (Kurilovas, 2016).

User experience strongly influences the acceptance of new technology (Kurilovas, 2016). The definition of *user experience* is the subjective, perceived knowledge and use of a technological product (Kurilovas, 2016) or “a person’s insight and response that is an outcome of usage or predicted usage of a system, product or service” (Kurilovas, 2016, p. 3). According to Kurilovas (2016), the successful adoption of new technology can be mitigated by a user-centered design approach in which the electronic products or services are designed, and support established “needs, concerns, and expectations of the possible end user” (p. 3). While the user’s knowledge is influenced by a range of learning experiences and practices, the user’s attitude is influenced by the perceived usefulness and ease of use in the user’s current surroundings (Kurilovas, 2016). Kurilovas explained how if a system was perceived as highly useful, users would be more inclined to acquire the knowledge necessary to use and accept the system. On the contrary, a system that was not perceived as useful, despite its ease of use, would not be accepted (Kurilovas, 2016). Fortunately, electronic data collection was the preferred data entry method and enhanced communication between educators and specialists, which promoted positive effects for students and educators (Kurz, 2018; Ruf, 2012). Knowledge of usefulness is key to user acceptance (Kurilovas, 2016) and implementing a successful technological data warehouse.

Conclusion

Data is transformative (Fernando, 2020), valuable (Shaked, 2010), and vital for the educational field (Wiseman & Bell, 2021). The twenty-first century is a “new era of turning data into more advantageous information to improve the accuracy of the decision-making process and adoption to face many challenges" (Fernando, 2020, p. 1). Research also supports the need for data collection and analyzation strategies and tools for ELD teachers to better understand the racial-ethnic achievement gap (Boyle et al., 2010; Wiseman & Bell, 2021; Fowler & Brown, 2018). Data practices in ELD are considered an exemplary TESOL practice (TESOL, 2023b), and would be a welcomed and necessary addition to the Federal ESSA program (Fowler & Brown, 2018; Wiseman & Bell, 2021; Garver, 2021). The need for data innovation in schools with large groups of minority and underserved students is overly evident when examining what is missing from the current data (Fowler & Brown, 2018) Furthermore, "utilizing data effectively will help address equity issues in terms of resource allocation… as accountability structures tangible increase student scores" (Fowler & Brown, 2018, p. 22). The first step to decreasing the racial-ethnic achievement gap is to collect and analyze data to better understand the current enacted practices in the educational system today (Wiseman & Bell, 2021; Kurz et al., 2015).

SECTION FOUR

CONTRIBUTION TO RESEARCH

Section Four exhibits the results of the present research study. First, an overview of the participant sampling will be provided to examine the demographics of the research participants. This section is divided into the research questions, and each will examine the statistical findings from the data collected pertaining to that question. Each of the three research questions was explored using quantitative statistical analysis as described in the methodology outlined in Section One. The research questions were:

1. What types of data do ELD educators report collecting and analyzing to modify instruction for English language learners?
2. What relationship exists between the number of years an educator has taught in an ELD program and how the educator reports collecting and analyzing data to modify instruction?
3. What relationship exists between the number of years an educator has taught in an ELD program and the way in which the educator reports on the *importance* of collecting and analyzing data to modify instruction?

The qualitative expansion questions from the survey will also be analyzed using a qualitative double-coding process, and the quantitative analysis of these findings will be presented:

30. In as much detail as possible, explain how you collect, use, and report data when making instructional decisions for ELLs in your school

31a. Have you ever participated in any of the following professional learning experiences [checklist provided]

31b. In as much detail as possible, explain the details of the professional learning you have experienced with data collection and analyzation.

All statistical calculations were completed through Google Sheets. This section is a summary of the results from all data collected from this present research. After the statistical findings are presented, the researcher will discuss the integration of these findings with the current literature.

Overview of Sampling Demographics

Upon endorsement from one of the high-incident[1] school districts, the study began on January 11, 2023, and the survey link remained open for responses for 31 days. During this duration, a second high-incident school district endorsed the research. The researcher also solicited participants via direct emails to their publicly listed school district email accounts, as outlined in Section One: Population and Sample. Of the 70 ELD teachers contacted, forty-three participants (*n* = 43) consented and completed the research survey. As displayed in Table 3, 65% of participants were ELD teachers in high-incident school districts, and 35% were ELD teachers in low-incident school districts. The following chart presents the complete demographics of the participant sampling. The majority of the sample was Caucasian, female, elementary educators from high-incident school districts. The participant sample was relatively equal in teaching experience and ranged from the first year of teaching ELD to 25 years of teaching.[2]

[1] As defined in Section One, the researcher considered high-incident school districts as any district with 10% or greater ELD enrollment; low-incident school districts contained less than 10% ELD enrollment.
[2] Length of teaching experience will also be referred to as teacher tenure.

Table 3

Overall Participant Demographics

Gender	Female	Male			
n	39	4			
%	91%	9%			
Race	Caucasian	Hispanic			
n	38	5			
%	88%	22%			
District	High-incident	Low-incident			
n	28	15			
%	65%	35%			
Grade	Elementary*	Middle	High	K-12	
n	22	11	3	7	
%	51%	26%	7%	16%	
ELD Tenure	1-5	6-10	11-15	16-20	21-25
n	10	12	9	7	5
%	23%	28%	21%	16%	12%
Age (years)	25-30	31-40	41-50	51-60	61-70
n	3	11	12	13	4
%	7%	26%	28%	30%	9%

*Within the classification of elementary level teachers, some teachers specified *upper elementary* (n = 3) or *lower elementary* (n = 7)

Table 4 presents further descriptive statistics of years teaching in ELD and the age (years) of the sample population. The average length of experience in ELD for the 43 respondents was 11 years, with a mode of 17 years. Six-to-ten years was the most common response for the length of experience teaching ELD. The mean of respondents' ages was 45.98 years, with a mode of 38 years. The respondents ranged from 25 to 68 years old, with 84% of educators between the ages of 31 and 60 years old.

Table 4

Descriptive Statistics for ELD Teaching Experience

	$\bar{x}$	$\tilde{x}$	Mo	R	*s*	*n*
ELD Tenure	11.09	10.00	17.00	24.00	10.81	43.00
Age (years)	45.98	44.50	38.00	43.00	6.78	43.00

Results of the Research Study

As described in the methodology outline of Section One, this research study examined the relationship between the independent variable (years of experience teaching in an ELD program) and the dependent variables (a) types of data educators use to modify instructional practices, (b) types of data analysis techniques educators use to modify instructional practices, and (c) educator perceived importance of data collection and analyzation. The following will examine each research question in comparison to these variables.

Question One: What types of data do ELD educators report collecting and analyzing to modify instruction for English language learners?

The purpose of *A Survey to Assess Data Use in Educational Decision Making* was to determine the data collected and analyzed by ELD educators. To answer this research question, participants responded to 14 questions in Section Four of the survey instrument by selecting *yes* or *no* to determine whether they used 14 specific types of data collection to modify their instructional processes. Section Four includes questions 7 through 20. Data collection types were split into three data categories: outcome data, perceptual data, and instructional process data. Questions 7 through 13 relate to outcome data. Questions 16 through 18 relate to perceptual data.

Questions 14, 15, 19, and 20 connect to instructional process data. These groupings are slightly different from the original research proposal due to a reassignment of (14) Attendance in ELD groups and (15) Discipline and Behavior being relocated to the instructional process data category rather than the outcome data grouping.

The overall data collection types for the sample (n = 43) were ordered into a frequency distribution and displayed in Table 5. Of the ELD teachers sampled, 100% (p = .10) reported collecting and using WIDA ACCESS scores to modify instruction. Other types of data collection that were frequently reported were *assessments developed by teachers* (88%) (p = .09) and *assessments developed by district* (84%) (p = .09). *Daily formative data: attendance* (84%) (p = .09), *documenting instructional strategies* (81%) (p = .08), and *instructional servicing time* (81%) (p = .08), were collected broadly as well. The least frequently collected data reported by the ELD teachers sampled were *student portfolios* (22%) (p = .05), *graduation rates* (35%) (p = .04), and *retention rates* (33%) (p = .03),

Table 5

Frequency Distribution for Data Collection

Data Collection Type	*n*	%	*p*
WIDA ACCESS scores	43	100%	.10
Classroom assessments developed by teachers	38	88%	.09
District student performance measures	36	84%	.09
Attendance in ELD groups or in-class support	36	84%	.09
Instructional servicing strategies	35	81%	.08
Instructional servicing time	35	81%	.08
Student discipline and behaviors	30	70%	.07
Perceptions of teachers in your school	30	70%	.07
Perceptions of students	30	70%	.07
Perceptions of parents	29	67%	.07
Standardized tests , i.e., state assessments	27	63%	.06
Student portfolios	22	51%	.05
Retention rates	15	35%	.04
Graduation rates	14	33%	.03

Tables 6.1, 6.2, and 6.3 display the average percentage of teachers that use each categorical type of data, as well as the probability of the frequency distribution. The results of these averages show that teachers reported using instructional process data most frequently (79%) (p = .25), as shown in Table 6.2. Outcome data was split into two calculation subcategories, performance data and demographic data. Demographic data was reported lowest from teacher participants (34%) (p = .50). In comparison, performance data was used by 77% of teacher respondents (p = .10). Perceptual data was reported to be used by 69% (p = .33) of surveyed teachers as displayed in Table 6.3.

Table 6.1

Outcome Data Usage

	Standardized tests	WIDA ACCESS scores	District student performance measures	Classroom assessments developed by teachers	Student portfolios	Retention rates	Graduation rates
$\bar{x}$	27	43	36	38	22	15	14
%	63%	100%	84%	88%	51%	35%	33%
p	.14	.22	.18	.19	.11	.08	.07
Total	$\bar{x}$	33.2				14.5	
	%	77%				34%	
	p	.10				.50	

Table 6.2

Instructional Process Data Usage

	Attendance in ELD groups or in-class support	Student discipline and behaviors	Instructional servicing model	Instructional servicing time
$\bar{x}$	36	30	35	35
%	84%	70%	81%	81%
p	.26	.22	.26	.26
Total	$\bar{x}$	34.00		
	%	79%		
	p	.25		

Table 6.3

Perceptual Data Usage

	Perceptions of parents	Perceptions of teachers	Perceptions of students
$\bar{x}$	29	30	30
%	67%	70%	70%
p	.33	.37	.37
Total	$\bar{x}$	29.66	
	%	69%	
	p	.33	

Section Five of the survey instrument included *yes* or *no* response questions regarding teachers' use of nine specific types of data analysis to modify their instructional processes. Section Five included questions 21 through 29. The data analysis results from Section Five of the survey were also ordered in frequency distribution and displayed in Table 7. The types of data analysis that were reported the most frequently were *charting the progress of individual students* (81%) (p = .18) and the *identification of trends and patterns over time* (74%) (p = .16). The least frequently analyzed data practices reported by the ELD teachers sampled were the *intersection of two* (21%) (p = .05), *three* (23%) (p = .05), or *four* (25%) (p = .06) types of data. Despite the low frequency of reported data analysis, 58% (p = .13) of ELD teachers responded affirmatively to *create reports based on the data analysis* to present their findings. Just 47% (p = .10) of ELD teachers reported *posing questions and analyzing data to find answers*.

Table 7

Frequency Distribution for Data Analysis

Data Analysis Types	n	%	p
Chart the progress of individual students	35	81%	.18
Identification of trends and patterns over time	32	74%	.16
Identification of trends and patterns at one point in time	27	63%	.14
Chart progress of subgroups of students	27	63%	.14
Create reports on the data analysis to present findings	25	58%	.13
Pose questions/hypotheses and analyze data to find answers	20	47%	.10
Intersect four types of data (i.e., how gender, attitude, and instructional strategies affect performance in English language development)	11	25%	.06
Intersect three types of data (i.e., how gender and attitude affect performance in English language development)	10	23%	.05
Intersect two types of data (i.e.. how gender affects performance in English language development)	9	21%	.05

Question Two: What relationship exists between the number of years an educator has taught in an ELD program and how the educator reports collecting and analyzing data to modify instruction?

The following null hypothesis was used to test research question two:

$H_0 1$: No statistically significant relationship exists between an educator's years of experience teaching in an English language development program and the types of data collected and analyzed to modify instruction.

The researcher performed the point biserial correlation coefficient (r_{pb}) to explore research question two and test hypothesis one. Like all correlation coefficients, the point biserial correlation coefficient measures the strength of the relationship between two variables and their association with each other (Creswell, 2017). The point biserial correlation quantitatively analyzes the effect of change in the continuous variable when the dichotomous variable *(yes* or *no)* changes. Similar to other correlation coefficients, point biserial coefficient values range from -1 to +1. Values closest to zero demonstrate no significant correlation between the variables. The point biserial r_{pb} was the best approach for this study because of the dichotomous variable and the goal to determine whether there was a significant correlation between the variables: years of teaching and types of data collected and analyzed. The point biserial correlation coefficient analysis was displayed in Table 8.1.

Table 8.1

Point Biserial Correlation Coefficient Analysis for Data Collection Types and Teacher Tenure[3]

	Standar-dized tests	District perform-ance measure	Class-room assessmen t	Student portfoli o	Retent-ion rate	Graduat-ion rate	Attend-ance in ELD group	Discip-line/ Behavio r	Percept-ion of parent	Percept-ion of teacher	Percept-ion of student	Instruct-ional servicing model	Instruct-ional servicing time
r_{pb}	.15	.19	.22	.25	.28	.23	.15	.14	.19	.25	.23	.25	.25
p	.34	.23	.13	.22	.10	.18	.34	.35	.22	.11	.14	.11	.11

In the present study, there was no statistically significant correlation between teacher years of experience teaching ELD and reported data collection, as displayed in Table 8.1. Based on the point biserial r_{pb} calculated, data collection practices had a very low, positive statistical correlation to teacher tenure in ELD. This result implies that teachers' length of teaching in ELD has no impact on their data collection practices. This study found no significant correlation between data collection practices for ELD teachers with less teaching experience and teachers

[3] The data collection type WIDA ACCESS is not reflected in this table on the condition of the correlational calculation error occurring due to every participant responding with a single response to a binary variable, rendering the correlational calculation impossible.

with more teaching experience. Therefore, the null hypothesis H_01 stating no statistically significant relationship exists between an ELD teacher's years of experience and the types of data collected and analyzed to modify instruction was not rejected.

Table 8.2

Point Biserial Correlation Coefficient Analysis for Data Collection Types continued…[4]

	Standar-dized tests	District perform-ance measure	Class-room assessme nt	Student portfolio	Retent-ion rate	Graduat-ion rate	Attend-ance in ELD group	Discip-line/ Behavior	Percept-ion of parent	Percept-ion of teacher	Percept-ion of student	Instruct-ional servicing model	Instruct-ional servicing time
Age	.20	.03	.49	.09	.18	.12	.45	.34	.29	.33	.25	.34	.34
p	.19	.82	.001	.56	.25	.43	.002	.03	.06	.03	.10	.03	.03
Grade	.27	-.16	.22	.23	.30	.34	.01	-.02	.20	.11	.11	.004	.004
p	.08	.29	.15	.13	.05	.02	.95	.88	.21	.47	.47	.98	.98
Import-ance	.55	.32	.53	.57	.47	.27	.51	.60	.71	.60	.71	.67	.67
p	.00	.03	.00	.00	.002	.07	.00	.00	.00	.00	.00	.00	.00
Gender	-.28	-.09	.11	.00	-.09	-.07	-.50	-.12	-.28	-.30	-.12	-.25	-.25
p	.10	.51	.46	.96	.67	.74	.00	.38	.06	.04	.38	.09	.09

Table 8.2, the researcher used the point biserial coefficient to examine the relationship between the data collection types and the other demographic data: age, grade, gender, and importance. There was a low, positive correlation between age and the data collection types. Age and classroom assessment correlated $r_{pb} = .49$ ($p = .001$). Age and attendance data correlated $r_{pb} = .45$ ($p = .002$). Grade level and gender had a very low correlation when tested with the data collection types. However, the data types collected variable had a moderate to strong positive correlation with the teachers' perceived importance. The following data types had the highest correlations: *perception of parents* ($r_{pb} = .71$) ($p < .00$), *perception of students* ($r_{pb} = .710$) ($p <$

[4] The data collection type WIDA ACCESS is not reflected in this table on the condition of the correlational calculation error occurring due to every participant responding with a single response to a binary variable, rendering the correlational calculation impossible.

.00), *instructional model* (r_{pb} = .67) (p < .00), *instructional time* (r_{pb} = .67) (p < .00), *behavior/discipline* (r_{pb} = .60) (p < .00), *student portfolios* (r_{pb} = .57) (p < .00), *standardized assessments* (r_{pb} = .55) (p < .00), *classroom assessments* (r_{pb} = .53) (p < .00), and *attendance in ELD groups* (r_{pb} = .51) (p < .00). These results indicated that ELD teachers' perceived importance of these data types impacts their usage of the corresponding data type in their data collection practices. No correlation was found differentiating performance, formative, and perceptual data as superior in relationship with any demographic category.

Table 9.1

Point Biserial Correlation Coefficient Analysis for Data Analyzation Types and Teacher Tenure

	Identify trends/ patterns over time	Identify trends/ patterns at 1 point in time	Chart progress of subgroups of students	Chart the progress of individual students	Intersect two types of data	Intersect three types of data	Intersect four types of data	Pose questions/ hypotheses and analyze data	Create reports based on the data analysis
r_{pb}	.13	.16	-.05	.31	.04	.07	.05	.23	.20
p	.41	.32	.76	.04	.78	.67	.76	.13	.19

Table 9.1 continues the point biserial correlation coefficient analysis (r_{pb}) for the types of data analysis in the survey for the present study. There was no statistically significant correlation between teacher years of experience teaching ELD and data analysis types reported to be used by ELD teachers. The correlation between teaching experience in ELD and data analysis frequency demonstrated a low, positive correlation for the analysis practice *chart the individual student's progress*. Based on the r_{pb} = .31 (p = .04), these results imply that teachers' length of teaching in ELD has a mild impact on their data analyzation practices. A point biserial r_{pb} correlation investigating the relationship between teachers' length of teaching in ELD and other data analysis types indicated a low, positive correlation. In this study, there were no significant data

analysis benefits for ELD teachers with less teaching experience than teachers with more teaching experience.

Table 9.2

Point Biserial Correlation Coefficient Analysis for Data Analyzation Types continued…

	Identify trends/ patterns over time	Identify trends/ patterns at 1 point in time	Chart progress of subgroups of students	Chart the progress of individual students	Intersect two types of data	Intersect three types of data	Intersect four types of data	Pose questions/ hypotheses and analyze data	Create reports based on data analysis
Age	.44	.26	.16	.51	.03	.22	.21	.32	.04
p	.003	.09	.29	.00	.84	.16	.17	.04	.81
Grade	-.01	.18	-.12	.004	.26	.36	.16	.10	.29
p	.93	.25	.43	.98	.09	.02	.31	.53	.05
Import-ance	.59	.46	.46	.59	.19	.33	.40	.30	.39
p	.00	.002	.002	.00	.22	.03	.01	.05	.01
Gender	-.18	-.08	-.08	-.26	-.16	-.18	-.19	.02	-.21
p	.25	.59	.59	.09	.29	.26	.23	.89	.17

The researcher continued to use the point biserial coefficient (r_{pb}) to examine the correlational relationship between the data analysis types and the other demographic data; age, grade, gender, and importance. Table 9.2 displayed the calculations from these analyses. There was a low, positive correlation between age and the data analysis types. Age and *identify trends and patterns over time* had a correlation of $r_{pb} = .44$ ($p = .003$). Grade level and gender also had a low, insignificant correlation when tested with the data analysis types. The types of data teachers reported analyzing had a moderate correlation with the perceived importance by the teachers in two categories of analysis: *identify trends and patterns over time* ($r_{pb} = .59$) ($p < .00$) and *chart progress of individual students* ($r_{pb} = .59$) ($p = .00$). These results imply that teachers' perceived importance of these data analysis types positively impacts their usage of that data type in their data analysis practices.

Question Three: What relationship exists between the number of years an educator has taught in an ELD program and the way in which the educator reports on the importance of collecting and analyzing data to modify instruction?

The following null hypothesis was developed to test research question three:

$H_0$2: No statistically significant relationship exists between an educator's years of experience teaching in an ELD program and the perceived importance of data collection and analyzation to modify instruction.

The researcher again performed the point biserial correlation coefficient (r_{pb}) to explore research question three and test hypothesis two. In addition to the findings on the correlational strength between the perceived importance and the data types collected, the third research question examines the relationship between years of teaching in ELD and the educators' perceived importance of data. Through a data efficacy meta-analysis, Gesel et al. (2021) found that perceived importance was greatly intertwined with data self-efficacy, affecting educators' data literacy and student outcomes. In the present study, an importance score was obtained by calculating the sum of each participant's responses to the questions on perceived importance. The perceived importance of the data collection questions were designed using a Likert scale and consisted of part *b* for questions 7-20. The maximum data collection perceived importance score was 70. The perceived importance of data analysis score was obtained by calculating the sum of all the Likert scale questions identified as part *b* for questions 21-29 for each participant, with a maximum score of 45. Most of the correlation analysis for these two variables was calculated using the Pearson product-moment correlation coefficient (r). This parametric calculation is used for circumstances where the independent and dependent variables are both continuous (Salkind & Frey, 2020). Both assigned perceived importance scores, teacher age, teaching tenure, and grades were continuous. Gender used the point biserial coefficient (r_{pb}) for calculations because of the dichotomous nature of the responses in this sample.

There was no statistically significant correlation between teachers' years of experience teaching ELD and the teachers' perceived importance of data collection and analysis, displayed in Table 10.1. Teaching experience in ELD did not correlate with the teachers' perceived data collection or analysis importance. This result implies that teachers' length of teaching in ELD does not impact their perceived importance of data collection or analysis. The results displayed in Tables 10.1 and 10.2 indicate a very low positive and nonsignificant correlation between teachers' tenure in ELD and teachers' perceived importance of data collection score ($r_{pb} = .14$) ($p = .37$) and analysis score ($r_{pb} = .10$) ($p = .54$). This study found no significant correlation between teachers' perceived importance of data collection or analysis for ELD teachers with less teaching experience and teachers with more teaching experience. Therefore, the null hypothesis $H_0 2$ stating that no statistically significant relationship exists between an ELD teacher's years of experience, and the perceived importance of data collected and analyzed to modify instruction was not rejected.

Table 10.1

Correlation of Data Collection Importance Score and Demographic

	Tenure	Age	Grade	Gender (r_{pb})
r	.14	.37	.26	-.08
p	.37	.01	.10	.60

Tables 10.1 and 10.2 display the calculations between the covariates and the teacher's perceived data importance. Educator age has a slightly higher, positive correlation with perceived data collection importance ($r_{pb} = .37$) ($p = .01$) and perceived data analysis importance ($r_{pb} = .35$) ($p = .02$). This correlation suggests that as a teacher's age increases, so does a teacher's perceived data importance.

Table 10.2

Correlation of Data Analysis Importance Score and Demographic

	Tenure	Age	Grade	Gender (r_{pb})
r	.10	.35	.10	.19
p	.54	.02	.51	.21

In Table 11.1, the researcher used the point biserial coefficient (r_{pb}) to examine the relationship between the perceived importance of data collection Likert response for each question and the demographic data; age, grade, and gender. There was a low, positive, and insignificant correlation between teacher age and the data collection types in every data collection category, except perceptual data. As displayed in Table 11.1, the age of teacher and parent perceptual data had a low, positive correlation of $r_{pb} = .40$ ($p = .01$). Age of teacher and *teacher perceptual* data had a low, positive correlation of $r_{pb} = .41$ ($p = .01$), and student self-concept *student perceptual* data had a low, positive correlation of $r_{pb} = .43$ ($p = .005$) (Figure 4). All other data collection and analysis options had a negligible correlation with the perceived importance corresponding to that data collection type. This low, positive correlation suggests that older teachers indicated more perceived importance for collecting perceptual data from parents, other teachers, and students. Figure 4 charts the correlation between teachers' age and the perceived importance of perceptual self-reflected student data. The correlation was negligible for the perceived importance of performance and formative data.

Table 11.1

Importance Response Point Biserial Correlation Coefficient for Data Collection Types

	Standar-dized tests	District perform-ance measure	Class-room assessm ent	Student portfolio	Retent-ion rate	Graduat-ion rate	Attend-ance in ELD group	Discip-line/ Behavio r	Percept-ion of parent	Percept-ion of teacher	Percept-ion of student	Instruct-ional servicin g model	Instruct-ional servicin g time	Standar-dized tests
Age	.22	-.28	.07	.37	-.09	.04	.15	.28	.36	.40	.41	.43	.33	.26
p	.16	.07	.67	.001	.54	.78	.34	.06	.02	.01	.01	.005	.03	.09
Grade	.14	.08	-.06	.05	.24	.35	.40	.02	.03	.23	.06	.23	.11	.07
p	.38	.59	.70	.74	.12	.02	.01	.87	.85	.14	.69	.13	.47	.64
Tenure	.003	-.22	-.07	.29	.05	.15	.23	.11	-.05	.19	.10	.04	.12	.09
p	.99	.16	.64	.06	.74	.34	.14	.47	.73	.21	.53	.80	.45	.55
Gender	.06	-.002	.04	.09	.14	-.05	-.09	-.10	-.21	-.13	-.22	-.16	.01	.00
p	.69	.99	.80	.55	.38	.73	.55	.51	.17	.39	.16	.31	.96	1.00

Figure 4

Teacher Tenure and Perceived Importance of Student Perceptual Data

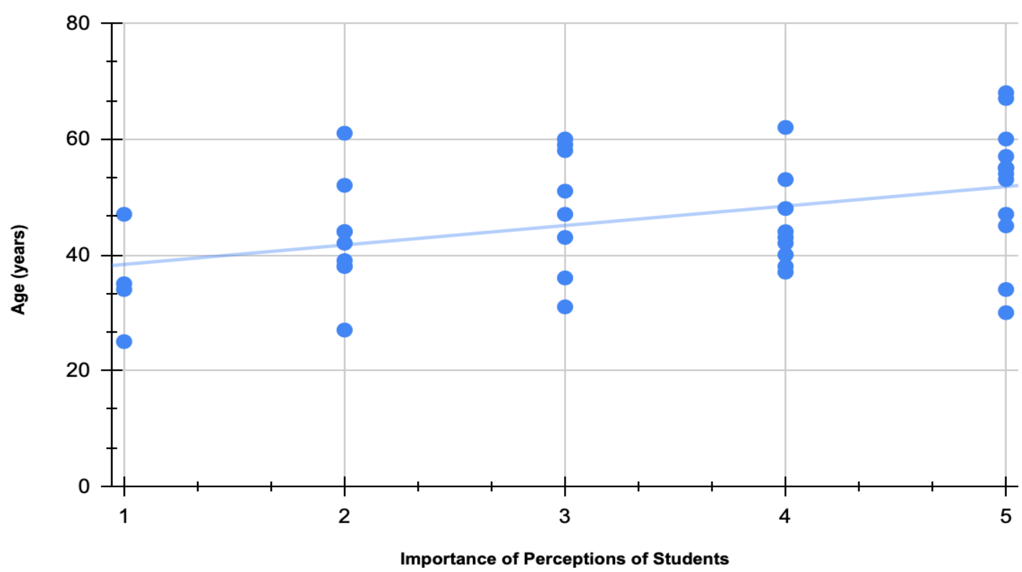


Table 11.2

Importance Response Point Biserial Correlation Coefficient for Data Analysis Continued…

	Identify trends/ patterns over time	Identify trends/ patterns at 1 point in time	Chart progress of subgroups of students	Chart the progress of individual students	Intersect two types of data	Intersect three types of data	Intersect four types of data	Pose questions/ hypotheses and analyze data	Create reports based on the data analysis
Age	.36	.31	.32	.38	-.09	.19	.32	.37	.17
p	.02	.04	.04	.01	.58	.21	.03	.01	.28
Grade	.06	.12	-.10	-.01	.17	.17	.12	.04	.13
p	.68	.44	.54	.94	.28	.26	.46	.78	.41
Tenure	.06	.06	.04	.18	-.18	-.14	.18	.15	.28
p	.70	.69	.78	.24	.26	.35	.25	.35	.07
Gender	-.21	-.04	-.01	-.33	-.20	-.11	-.11	-.04	-.26
p	.19	.81	.94	.03	.19	.48	.47	.82	.09

Expansion Questions

Three final expansion questions were asked at the conclusion of the survey instrument. A total of three follow-up questions were asked;

30. In as much detail as possible, explain how you collect, use, and report data when making instructional decisions for ELLs in your school.

31a. Have you ever participated in any of the following:

- Professional Development of Data Collection
- Professional Development of Data Analyzation
- Data-Driven Community Practice
- College Course on Data Collection and Analyzation
- A Workshop or Seminar on Data Collection and Analyzation

31b. In as much detail as possible, explain the details of the professional learning you have experienced with data collection and analyzation.

Questions 30 and 31b were analyzed for themes and trends using inductive data analysis. Saldaña's (2021) Descriptive Coding techniques were used to derive descriptive measures from the themes on the Qualitative Dedoose app. The following pre-established themes were analyzed: *data collection techniques*, *data analyzation techniques*, *data collection importance*, *and data analyzation importance*. The second coding cycle used Saldaña's focused coding to further clarify and emphasize the themes and visualizations. The analyzation of the codes was done through quantitative descriptive statistics. Question 31b was analyzed similarly to the three research questions above using a correlational analysis. The participant responses entered into the survey instrument can be found in Appendix F (Question 30) and Appendix G (Question 31b).

After coding the first level of themes, the researcher used Saldaña's focused coding to determine the most frequent response for data collection, data analysis, and data importance. Figure 5.1 is a word cloud for the participants' most common data collection responses on the first open-ended question. In the word cloud design, larger words represent responses with a higher frequency. Figure 5.2 gives the numerical values for the same data set. WIDA ACCESS showed up the most frequently, reported by 24 respondents (56%). Summative assessments (standardized and/or state assessments) were used as a focused code category and found in the responses of 12 participants (28%). District assessments were referenced in 15 responses (35%). The focused codes that were referenced less frequently were student perspectives, portfolios, and attendance, each with only two responses (5%).

Figure 5.1

Qualitative Data Collection Techniques Word Cloud

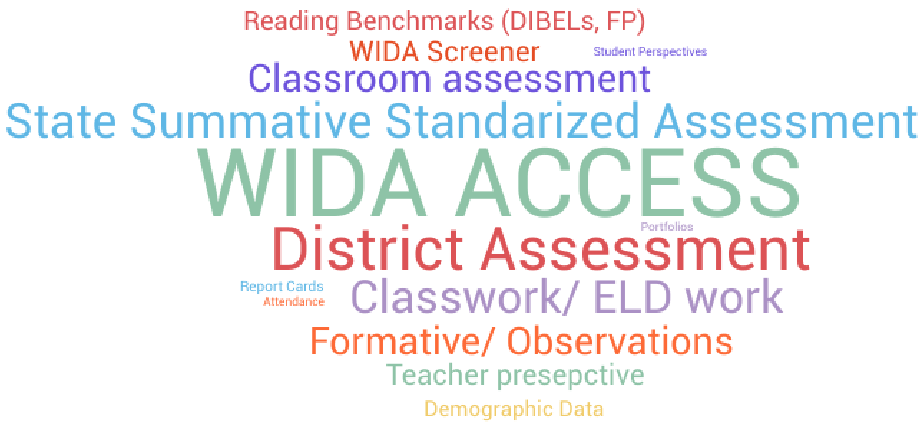
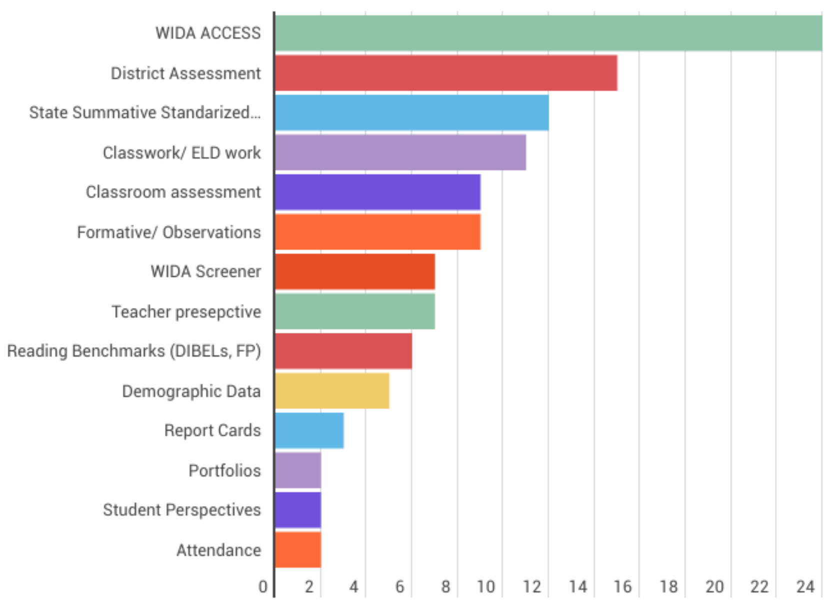


Figure 5.2

Qualitative Data Collection Techniques Bar Graph



Most of the 116 data collection references were categorized into the 14 codes in the secondary coding process. While Figures 5.1 and 5.2 outlined many of the focused codes, a few singular responses remained outliers. *Temperament*, *English language plans,* and *language goals* are among some of the least frequent responses by teachers when reporting openly on their data collection practices.

When asked to respond openly about data collection and analyzation practices, the focused codes for data analysis references appeared less frequent in comparison to data collection references. Only nine focused codes were created for 45 references, as represented visually in Figure 6.1 and numerically in Figure 6.2. The most frequent data analysis references were *collaboration* with 13 references (30%), ‘monitor progress over time’ with 11 references (26%), and ‘document with charts, graphs, reports, or spreadsheets’ had seven responses (16%). The least frequent reference was to intersect multiple data points with one reference (2%). The focused codes *analyzing the needs of students* and *analyzing their own teaching* both had two references (5%). One respondent strongly called for “more frequent data analysis”, but this response did not fit into a focused code of a data analysis type.

Figure 6.1

Qualitative Data Analysis Techniques Word Cloud

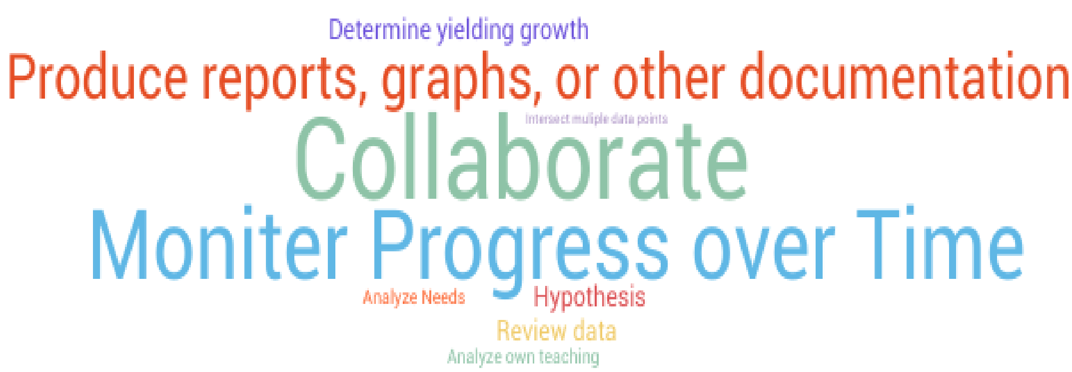
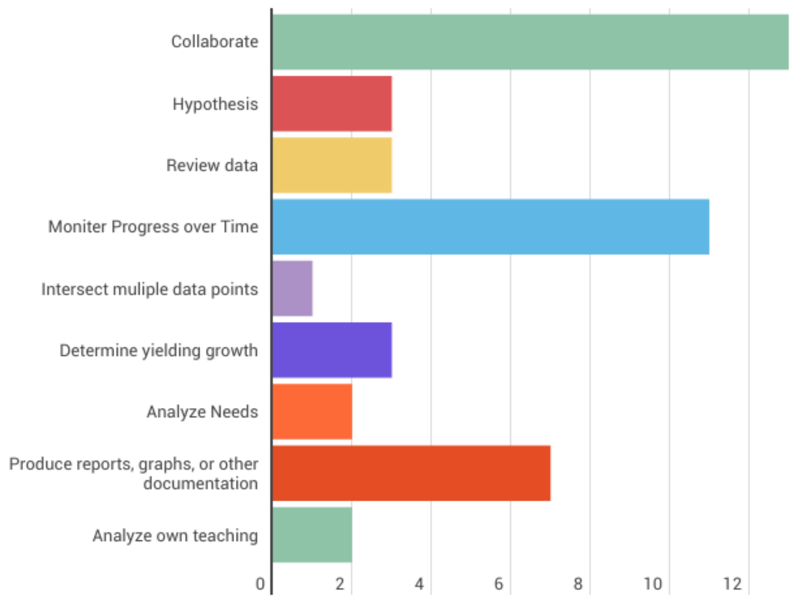


Figure 6.2

Qualitative Data Analysis Techniques Bar Graph



The last theme of the primary coding for the first open-ended question was *data collection and analysis importance.* The secondary focus coding contained 68 references split into ten codes that fit into two divergent categories; data supportive (46) or data negligent (22). Tables 7.1 and 7.2 display the results of the focused code analysis for Question 30. Nineteen teachers directly referenced the importance of data collection and analysis to inform instruction (44%). Similarly, 11 teachers referenced the importance of data for the purpose of informing groupings. of students (26%). Of the data-supportive codes, three teachers referenced that "the more data, the better", with very similar wording (7%), and two teachers indicated the importance of using data in their professional self-reflection practices (5%). One of the data-supportive participants wrote,

> "Data collection and analysis are important parts of instructional decisions, and I always use data to drive my instruction. Instructional decisions are always complete decisions

that require the analysis of data, along with professional judgment and observations of students' work and progress."

This quotation demonstrates this participant's importance and emphasis on data in their ELD practices.

Figure 7.1

Qualitative Data Importance Word Cloud

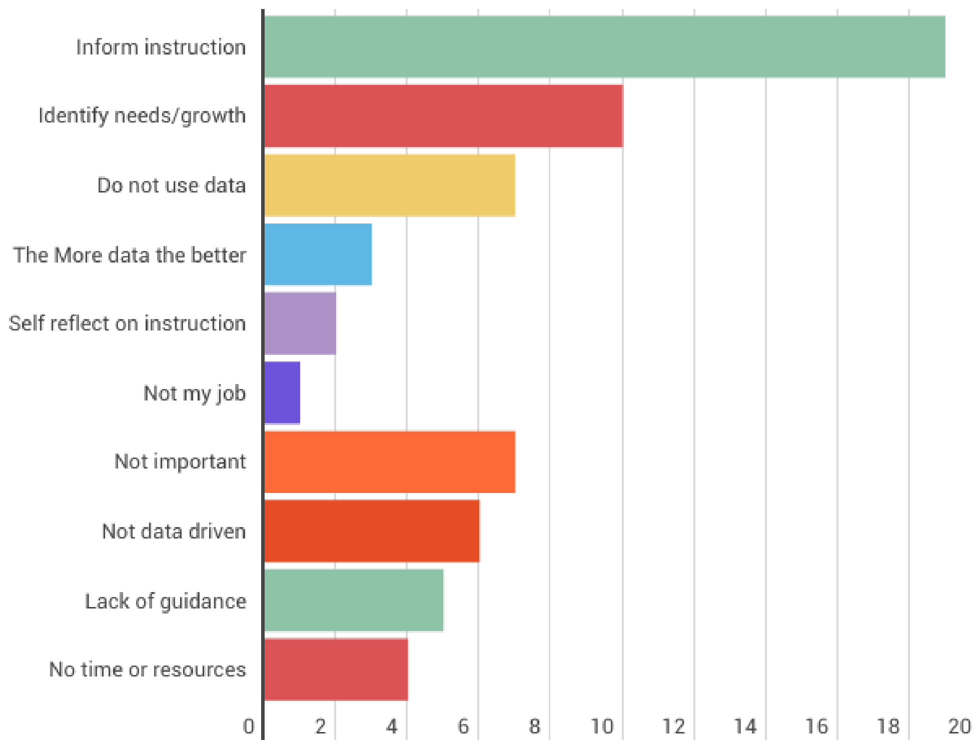
Conversely, the five data-negligent codes were extracted from the data importance-themed responses. 'Lack of data use' and 'lack of data importance' each held seven references in the responses (16%). Specifying, participants credited a 'lack of time and resources' (*n* = 4) (9%), 'lack of guidance from district and state' (*n* = 5) (12%), 'lack of data-driven identity' (*n* = 6) (14%), and one teacher stated that "it is not my job" (2%). Another participant wrote, "I am cautious to make many generalizations about what data says about ELs in general since they are such a diverse group of students". Another third participant responded,

"I also find it frustrating that our instructional services are dictated by ACCESS score only- a set of data that is 6+ months old by the time we use it. Personally, and as a district, we are working toward finding quick and easy to collect data to track student progress and achievement. Often this data is not shared with classroom teachers unless something is alarming."

Multiple teachers described the hindrances to data collection, including lack of support, guidance, and one teacher referenced data collection as a "recommendation".

Figure 7.2

Qualitative Data Importance Bar Graph



Questions 31a and 31b focus on professional learning (PL) experiences in data collection and analyzation. In Section Three, the literature review presented consistent results regarding the connection between PL experiences in data collection and analysis and data efficacy. Dunn et al. (2013) identified PL experiences as one factor contributing to data efficacy, which transferred to student achievement. Question 31a provided participants with five different examples of professional development teachers might have received on the topic of data collection and analyzation: professional development of data collection, professional development of data analyzation, data-driven community practice, a college course on data collection and analyzation, or a workshop or seminar on data collection and analyzation. The data compiled from this question was numerical and analyzed quantitatively using descriptive and inferential statistics. Figure 8 displays the frequency distribution for the PL experiences category. PL data collection was reported by 19 participants (44%). Conversely, 11 participants reported experiencing none of the PL categories (26%). Fifteen participants reported PL of data analyzation (35%), data-driven community practice (35%), and a workshop or seminar on data collection and analyzation (35%).

The descriptive statistics of the PL experiences displayed in Table 12, depicts the range of responses from the survey question. Based on the responses of the 42 participants, the mean of the PL experiences was 1.721. The mode was zero PL experiences, the median was one experience, and there was a range of responses from zero to five experiences. The standard deviation for the PL experiences was 1.62.

Figure 8

PL Experience Frequency

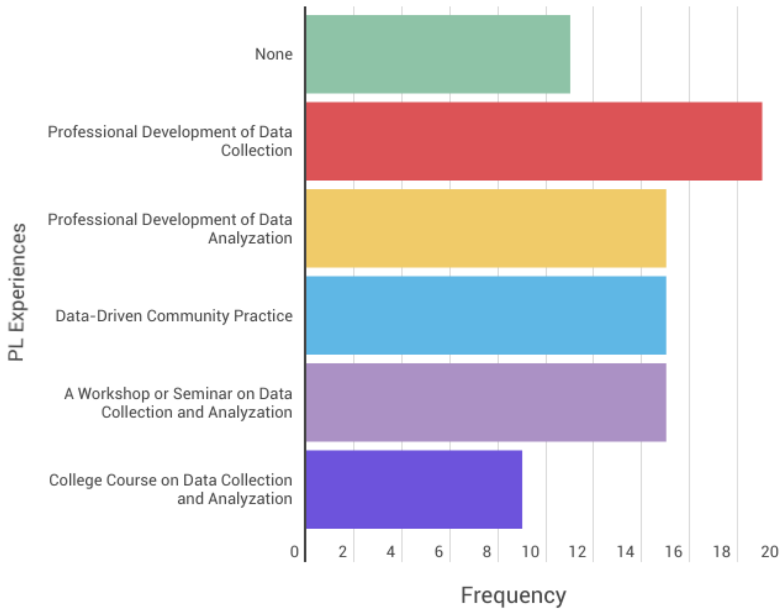


Table 12

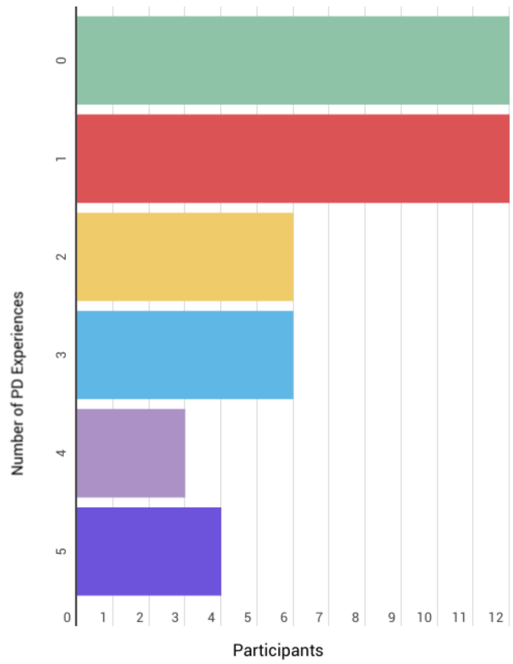
Descriptive Statistics of PL Experiences

	$\bar{x}$	$\tilde{x}$	Mo	R	*s*	*n*
PL Experiences	1.72	1	0	5	1.62	43.00

Figure 9 displays the frequency in which the ELD teachers reported participating in one of the PL options. Twelve teachers reported never receiving any of the data collection and analyzation PL experiences (30%) and twelve teachers reported only receiving one data collection and analyzation PL experience (30%). Nine teachers reported receiving 4-5 of the data collection and analyzation PL experiences (21%).

Figure 9

Frequency Participants Experienced Data Collection and Analyzation PL



A PL score was assigned to each participant based on their responses. For each time type of PL experience an ELD teacher reported to have received, the participant was given a point (max: 5). This score and the data collection and analyzation types were then used to calculate correlation using a point-biserial correlation coefficient (r_{pb}). Tables 13.1 and 13.2 show the relationship between the PL scores and the data collection and analysis types in the research survey. All the data collection types demonstrated a negligible correlation with the participants' PL score. The correlation was slightly higher between the data analyzation and PL score. The correlation between the PL score and *charting progress of individual students* was $r_{pb} = .40$ ($p = .01$). Similarly, the correlation between the PL score, *posing questions or hypotheses, and analyzing data* was $r_{pb} = .42$ ($p = .005$). While these calculations are still considered low, positive correlations, this finding suggests that the more PL experiences an ELD teacher has, the more likely they are to chart the progress of students, pose questions, and analyze the data. The correlation between the PL score and the perceived importance score also showed a negligent correlation (r_{pb} = .06) ($p > .05$).

Table 13.1

Point Biserial Correlation Between Data Collection Types and PL Score[5]

	Standar-dized tests	District perform-ance measure	Class-room assessme nt	Student portfolio	Retent-ion rate	Graduat-ion rate	Attend-ance in ELD group	Discip-line/ Behavior	Percept-ion of parent	Percept-ion of teacher	Percept-ion of student	Instruct-ional servicing model	Instruct-ional servicing time
r_{pb}	.20	.11	.30	.15	.19	.18	.28	.17	.19	.11	.17	.21	.21
p	.21	.53	.05	.34	.23	.24	.07	.28	.23	.50	.28	.17	.17

Table 13.2

Point Biserial Correlation Between Data Analyzation Types and PL Score

	Identify trends/ patterns over time	Identify trends/ patterns at 1 point in time	Chart progress of subgroups of students	Chart the progress of individual students	Intersect two types of data	Intersect three types of data	Intersect four types of data	Pose questions/ hypotheses and analyze data	Create reports based on data analysis
r_{pb}	.30	.32	.23	.40	.02	.10	.07	.42	.18
p	.05	.04	.14	.01	.91	.54	.66	.005	0.26

Question 31b was an open-ended response opportunity for participants to describe their professional development experiences in further detail. The research used Saldaña's (2021) two-phase coding process to analyze responses. The thematic codes were identified more broadly in the first phase of coding and then focused coding was used during the second phase of analyzation.

In the first phase of thematic coding, the following codes were identified for data

[5] The data collection type WIDA ACCESS is not reflected in this table on the condition of the correlational calculation error occurring due to every participant responding with a single response to a binary variable, rendering the correlational calculation impossible.

collection and analyzation PL experiences: state-level PL, district PL communities, no data PL, college courses, WIDA PL courses, and personal research. The responses were analyzed for frequency and detail during the secondary-focused coding. Figure 10.1 displayed the codes in a word cloud, visually representing the frequency based on the sizes of the words.

Figure 10.1

Qualitative PL Experiences Word Cloud

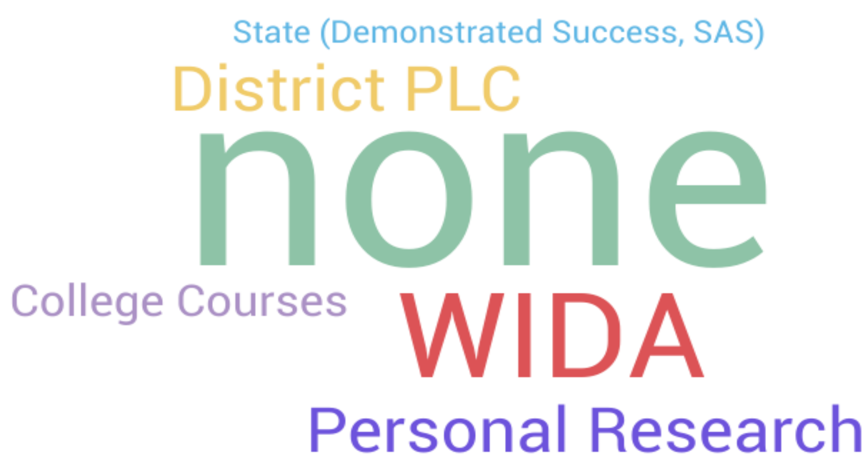
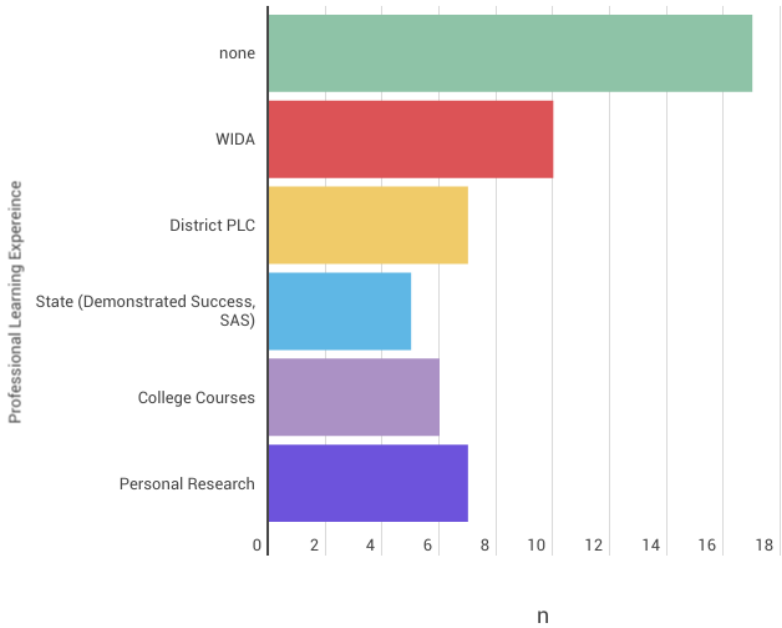


Figure 10.2 displayed the numerical representation of the codes. In reference to the PL experienced as an ELD teacher, the most frequent response was *none* (n = 17) (40%). The types of PL that the ELD teacher respondents had experienced were WIDA PL courses (n = 10) (23%), district PL communities (n = 7) (16%), college courses (n = 6) (14%), and state-level PL (n = 5) (12%). Personal research on data collection and analyzation were reported by 7 participants (16%).

Figure 10.2

Qualitative PL Experiences Bar Graph



The direct written responses from the teacher participants varied greatly. Some teachers used a “0”, “none”, or “no” to refer to not experiencing PL on data collection and analyzation. Other responses were more expanded like, “not enough to make the decisions needed to successfully support students”. Another distinction was that the data-driven PL was offered, but not specific for the needs and practices of ELD teachers, as in the following written response, “Data collection and analyses are not regularly offered for ELL teachers”. Another response echoed a similar need for ELD-specific PL but using an omission approach.

> “While this is my first year as an ELL teacher. I have taught SpEd for 22 years. I have taken courses as well as on-going workshops on data collection and analysis. I was part of a data team at one of my schools for 3 years - we met to review SAS test scores for the entire building and determine areas of weakness in order to help classroom teachers

> improve their instruction in those areas…I also worked closely with the Reading specialist, every year, to review grade level data and determine the students who needed intervention as well as the type of intervention needed We then designed groups to focus on those needs. Typically, we review data collection and its importance to use the data to drive instruction on an early basis at a faculty meeting. It is up to the individual to seek out professional learning in this area on their own."

This example provided cause to consider previous data collection and analyzation experiences as PL influencing current practices. However, for a participant who describes themself with such data fluency, the omission is the lack of mention of current data practices used in ELD over their past year or how their data fluency translates to their new role.

Conclusion of Statistical Significance

As outlined in Section One: Methodology, the researcher explored the relationship between the length of teaching experience in ELD and data collection and analyzation types, and ELD teacher perceived importance of data collection and analyzation. Based on these variables, three research questions were explored through statistical data analysis, and two null hypotheses were tested. *A Survey for Assessing the Data Used by Teachers* was taken by 43 voluntary teacher participants from New Hampshire public schools. The participant sample was analyzed using descriptive statistics.

Question one explored the data collection and analyzation practices with a frequency distribution. WIDA ACCESS scores were the most widely used data collection type, reported by 100% of the ELD teachers in the participant pool. *Charting the progress of individual students* was the most widely used data analyzation practice, reported by 81% of the ELD teachers in the participant pool. Question two explored the relationship between the length of ELD teaching experience and data collection and analyzation practices. Using the point-biserial r_{pb}, a nonsignificant correlational relationship was calculated between

- the length of ELD teaching experience and data collection
- the length of ELD teaching experience and data analyzation.

The null hypothesis H_01 stating that no statistically significant relationship exists between an ELD teacher's years of experience and the types of data collected and analyzed to modify instruction was not rejected.

The researcher also explored the relationship between data collection and analyzation and the other demographic data collected through the survey. The types of data collected had a moderate to strong correlation with the teachers' perceived importance of data, especially in the following data collection categories: *perception of parents* ($r_{pb} = .71$), *perception of students* ($r_{pb} = .71$), *instructional model* ($r_{pb} = .67$), *instructional time* ($r_{pb} = .67$), *behavior/discipline* ($r_{pb} = .60$), student portfolios ($r_{pb} = .57$), *standardized assessments* ($r_{pb} = .55$), *classroom assessments* ($r_{pb} = .53$), and *attendance in ELD groups* ($r_{pb} = .51$). The types of data teachers reported analyzing had a moderate correlation with the ELD teachers' perceived importance in *identifying trends and patterns over time* ($r_{pb} = .59$) and *charting the progress of individual students* ($r_{pb} = .59$). A negligible correlation was established with all other correlations tested for data analyzation.

Question three explored the relationship between the length of ELD teaching experience and teachers' perceived importance of data collection and analyzation. Using the point-biserial r_{pb}, no statistically significant relationship was found. The null hypothesis H_02 stating that no statistically significant relationship exists between an ELD teacher's years of experience and the perceived importance of data collected and analyzed to modify instruction was not rejected.

Using the perceived importance score, educator age was the only covariant with a low, positive correlation to perceived data collection importance ($r_{pb} = .37$) and perceived data analysis importance ($r_{pb} = .35$). When measuring the relationship between teacher age and the individual data collection importance ratings, the perception of parents ($r_{pb} = .40$), teachers ($r_{pb} = .41$), and students ($r_{pb} = .43$) all measured a low correlation.

Lastly, three open-ended expansion questions were analyzed in addition to the three research questions and two null hypotheses. The first open-ended research question asked participants to expand on their data collection and analyzation practices. The responses went through a two-phase thematic coding process. The most frequent data collection practice reported was WIDA ACCESS (n = 24) (56%), summative assessments (standardized or state assessments) (n = 12) (28%), and district assessments (n = 15) (35%). The most frequent data analysis practices reported were collaborating (n = 13) (30%), monitoring progress over time (n = 11) (26%), and documenting with charts, graphs, reports, or spreadsheets (n = 7) (16%). The final coding category explored data collection and analyzation perceived importance and found 46 data supportive remarks or 22 data negligent remarks. The importance of data collection and analyzation for informing instruction was reported the most frequently (n = 19) (44%). Of the data negligent remarks, lack of data use (n = 7) (16%) and lack of data importance (n = 7) (16%) were reported the most often. Participants also reported a lack of data-driven identity (n = 6) (14%), guidance from the district and state (n = 5) (12%), and time and resources (n = 4) (9%).

The second expansion question included a closed, checkbox response and an open-ended response on professional learning (PL) experiences. Five PL experiences were given as options for participants to check if they had experienced that category of PL. Analyzed quantitatively, professional development on data collection was the most frequently reported PL experience (n =

19) (44%). However, 11 participants responded to receiving none of the PL experiences (26%). Most participants reported experiencing 0-1 PL experience (n = 24) (56%), and the mean of the data-focused PL experiences was 1.721. Based on the total PL experiences reported, a PL score was calculated for each participant. When this PL score was used to calculate a point-biserial correlation with each data collection and analyzation types, a low, positive correlation existed between the PL score and *charting progress of individual students* (r_{pb} = .40) and *posing questions or hypotheses and analyzing data* (r_{pb} = .42). Nonsignificant correlations were calculated between all the other data collection and analyzation categories.

The second and final open-ended research question asked participants to expand on their PL experience. The responses also went through a two-phase thematic coding process. Seventeen participants reported no data-focused PL experiences (40%), followed by WIDA PL courses (n = 10) (23%), district PL communities (n = 7) (16%), and personal data-focused research (n = 7) (16%). The complete compilation of the above statistical findings allowed the researcher to analyze the enacted limitations of the present research and suggest implications.

Limitations

No research study is without limitations. After analyzing the findings, the present research demonstrated a limitation. First, based on the limited findings in Section Three on data collection and analyzation practices for ELD programs, the researcher determined a gap in the research (Wiseman & Bell, 2021; Fernando, 2020). This gap suggested minimal or discordant practices of data collection and analyzation in ELD. The present findings further emphasized this assumption. Accepting this assumption would also imply that with minimal or desynced data collection and analyzation practices occurring, and ELD teacher participants might struggle to accurately account for their data and analyzation practices in uniform language or report the quality and quantity of their practices as they might relate to others.

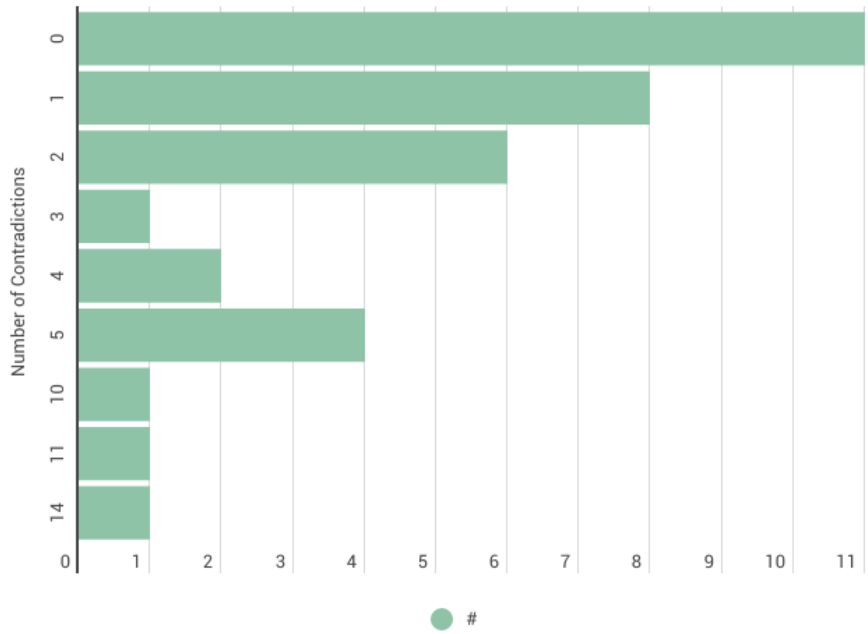
Accuracy is a data quality concern of the utmost importance in factual surveys, like the one used in the present study (Singh, 2011). The research found at least one inaccuracy in thirty-two participant surveys. This limitation is evident in the present research because multiple teacher participants contradicted their responses. For example, a respondent reported collecting and analyzing types of data in Section Three, but reported collecting and using data differently in the open-ended response to Question 30. For this sub calculation, the criteria for an *inaccuracy* to be considered are as follows;

1. Participant response in one category was opposite of another category (i.e., the participant responded to using 12/14 of the data collection types, but the same participant stated "I only use WIDA data" in their open-end response).
2. Participant responded *yes* or *no* to collecting or analyzing a data type, but responds in an opposite nature to the importance of that data collection or analyzation type (i.e., the participant responds that they do not collect standardized test score data, but they rank the perceived importance highly with a Likert score 4 or 5).

Figure 11 displayed the frequency of the contradictions present in the research. Twenty-four teacher participants had at least one contradiction in their survey responses (56%). Seven teacher participants had two-to-three response contradictions in their survey responses (16%). Six teacher participants had four or five contradictions in their survey responses (14%). In three surveys, 10, 11, and 14 contradictions were found.

Figure 11

Contradiction Frequency



According to Singh (2011), “In most cases, no particular ‘theory’ provides explanations as to why respondents might choose to report inaccurately to factual questions in a survey” (p. 53). However, respondent accuracy was less reliable on judgments of the past (Cahalan, 1968) and the most and least frequent events (Rowen et al., 2004). Cahalan (1968) found that the most common reasons for accuracy errors were: (a) chance, (b) persistent forecast, (c) status-induced errors, (d) stemming from identity issues, and (e) from interactions between respondents and researchers. Singh (2011) explained that many cognitive processes are activated during survey research, which Tourangeau et al. (2000) identified as a four-step process: “interpretation of meaning and intent of each question, retrieval of relevant information from memory, use the retrieved information for creating a summary judgment, report the judgment considering available alternatives” (as cited by Singh, 2011, p. 51).

SECTION FIVE

IMPLICATIONS AND CONTRIBUTION TO SCHOLARSHIP AND PRACTICE

The present research offers findings that begin to fill a gap in research and literature on data collection and analyzation in ELD programs. In Section Five, the researcher will merge the current literature and these findings to discuss conclusions and how these conclusions will contribute to both scholarship and practice.

Summary

The present quantitative correlational survey study aimed to explore the importance of data collection and analysis practices for New Hampshire ELD educators using the data-driven decision-making (DDDM) framework by Mandinach et al. (2006). At this phase of the research, data collection and analyzation in ELD can be generally defined as how teachers: (a) compile, organize, and document ELD learning opportunities and growth monitoring with students, (b) use data in a meaningful way to guide instruction, and (c) create reports on the data collected effectively for the betterment of the students. The definition was adapted to include recognizing the role that growth monitoring plays in data collection and analyzation, as evident in the literature and the present study findings. The actional framework supporting this definition, DDDM, is the process of identifying data, collecting it to be analyzed and interpreted, and using it to set goals to improve educational experiences (Mandinach & Schildkamp, 2021a).

The present study explored the relationship between the independent variable, length of ELD teaching experience, and the dependent variable, teacher self-reported data collection and analyzation practices and teacher-perceived importance of data, through a cross-sectional survey and correlational analysis. These variables were explored using three research questions and two null hypotheses. Modeled after previous research by Zigmund (2020) and Cronin (2001), the survey, *A Survey for Assessing the Data Used by Teachers,* was used to collect data from 42 voluntary ELD teacher participants from New Hampshire public schools.

The participant sample was likely more engaged members of the ELD community based on their willingness to self-reflect on their data-driven practices and complete the research survey (Singh, 2011). The participants were analyzed using descriptive statistics and found to be primarily Caucasian women in high-incident, elementary school settings between the ages of 31 and 60. The demographic profile of the teachers in the present study closely mirrors the national averages. Based on 2017-2018 education statistical data, 76% of teachers in the United States are women (NCES, 2020). Seventy-nine percent are Caucasian, and 9% are Hispanic (NCES, 2020). According to NCES (2020), the national average age is 42.4 years old, which compares closely to the participant sample of the present study average, 45.98 years old. According to the responses in the present research, the average length of ELD teaching experience was approximately 11 years, which was lower than the national average of 15 or more years of teacher tenure (NCES, 2020). The following discussion of conclusions is a merger of the statistical findings from the present study and the previous literature available.

Discussion

Conclusion One: Data Analysis Decline

Data was collected by ELD teachers, but not analyzed or used as knowledge at the same rate. The DDDM framework by Mandinach et al. (2006) delineates the flow of data from raw to collection, information (analyzation), and knowledge. The present study discovered a decreasing phenomenon between the data collection and analyzation processes. The researcher used a frequency distribution to analyze the data collection and analyzation practices reported by the ELD teacher respondents. Over 50% of the ELD teachers reported using 12 of the 14 data collection types, with 70% of participants using nine of the 14 data collection practices. Only 5 of the 9 data analysis practices were participated in by 50% or greater of the ELD teacher sample, and two of the nine data analysis practices were used by more than 70% of the participants. These findings demonstrated a 42% decrease in data usage for the ELD teachers who reported 50% or greater usage and a 30% decrease for ELD teachers who reported 70% or greater usage. The discoveries from the open-ended qualitative data added a narrative voice to the numerical rigidity of the statistical analysis (Creswell & Creswell, 2018) and confirmed this conclusion. Of the 161 data collection and analyzation responses, 72% referenced data collection, and 28% referenced data analyzation, furthering the concern regarding the decreasing data being analyzed and used to inform knowledge (Mandinach et al., 2006).

Despite the data usage recommendations of TESOL (TESOL, 2023c) and prior research supporting educational data (Dodman et al., 2021; Mandinach & Schildkamp, 2021b), previous literature described educational data for ELLs as “anecdotal, limited in scope, or related to population size rather than disaggregate-able experiences” (Wiseman & Bell, 2021, p. 2). A data description that is not analyzable. Further elaborating on the concerns, Wiseman and Bell determined language data was the only educational data often available on ELLs, to which Fowler and Brown (2018) added the worrisome achievement data records and standardized assessments. Beyond language data, which references the language proficiency scores on an annual exam, such as the WIDA ACCESS, or state, standardized assessment data, little is revealed in research on the data collection and analyzation practices of ELD teachers. The scarcity of ELD data collection in the literature was not consistent with the findings in the present study, rather the lack of data practices present in the literature could suggest a possible influence for the declining data practices between collection and analyzation. Historically, if a shortage of ELD data collection practices existed, then the subsequent process of ELD data analysis practices was less relevant. Unfortunately, even if data collection increased, ELD teachers could lack the necessary knowledge and skills to analyze the collected data.

WIDA. Of the data ELD teachers collected, WIDA ACCESS scores were reported by 100% of participants and made up the largest qualitative code from the open-ended responses. This finding is consistent with current research (Wiseman & Bell, 2021), and the directives of the WIDA consortium, of which New Hampshire is a part (WIDA, 2022). According to WIDA (2022), New Hampshire approved the use of the WIDA ACCESS for all identified ELLs, and according to the NHED's Bureau of Instructional Support: ESOL K-12- English for Speakers of Other Languages division, the WIDA ACCESS administration is mandated by federal law (NHED, 2022). This annual language proficiency assessment is the most widely accepted and used form of data collection and reporting in Title III (Coulter, 2016). Unsurprisingly, this research finding demonstrates high compliance (100%) with this data collection standard, mirroring the national and state-level literature.

As for data analyzation practices revealed in this study, *charting the progress of individual students* was the most widely used practice, reported by 81% of the ELD teachers. The data analysis methods for WIDA ACCESS possibly influenced this finding. WIDA produces a score report chart every year with students' rankings. These reports were referenced by 65% of ELD teachers collectively between their two open-end responses. WIDA provides a variety of professional learning sessions and resources for ELD educators around WIDA administration, scoring, and disseminating the score data reports (WIDA, 2022). Among these resources, a nineteen-page *ACCESS for ELLs Interpretive Guide for Score Reports* provides in-depth descriptions and applications for understanding and using these reports. An excerpt from this manual is shown in Figure 12.

Figure 12

Excerpt from the ACCESS for ELLs Interpretive Guide for Score Reports

Composite Scores

In addition to proficiency level and scale scores for each language domain, students receive a proficiency level score and a scale score for different combinations of the language domains. These composite scores are Oral Language, Literacy, Comprehension, and Overall.

Proficiency levels are always calculated from scale scores. For example, the Reading and Writing scale scores are averaged to create a Literacy scale score. Here, a 359 in Reading and a 353 in Writing would result in a Literacy scale score of 356. The Literacy scale score is then associated with the Literacy proficiency level.

Language Domain	Proficiency Level (Possible 1.0-6.0)	Scale Score (Possible 100-600) and Confidence Band See Interpretive Guide for Score Reports for definitions
Listening		
Oral Language 50% Listening + 50% Speaking		
Literacy 50% Reading + 50% Writing	3.5	356
Comprehension 70% Reading + 30% Listening	3.7	360
Overall* 35% Reading + 35% Writing + 15% Listening + 15% Speaking	3.4	352

(WIDA, 2023, p. 7)

This interpretive training guide provides an example of the PL that New Hampshire ELD teachers regularly experience through the WIDA Consortium membership and a possible explanation for the high reporting of data analyzation practice of charting progress for individual students.

WIDA data collection consists of a mandated annual language proficiency exam. ELD teachers are trained to use the supplied language proficiency reports as knowledge and justification for instructional decision making. The analyzation of the language proficiency data is effortless for ELD educators. Therefore, though WIDA ACCESS data is collected without fault and frequently used to make decisions, the lack of active teacher engagement and cognition that goes into the DDDM process is minimal. Duhigg (2016) found effortless data interpretation systems less valuable to teachers due to the lack of cognitive disfluency. Cognitive disfluency is the process of making something more challenging, triggering the brain's processing speed to slow, resulting in more careful and in-depth observation. Duhigg (2016) maintained the acute importance of data, but only with intentional interpretations and active engagement with the data. When Duhigg removed a data dashboard with passive data interpretation and guided teachers in more data-rich practices employing cognitive disfluency, teachers were more successful and confident with DDDM. Suppose WIDA could allow teachers to take a more active role in the analysis of the data already so readily collected. In that case, this could help teachers begin to value information processing and use these skills across other types of data collection.

Consistent with the present findings, Namvar and Intezari (2021) found that analytics were often vague and rarely an essential part of the DDDM process. Teachers needed to be able to manipulate and disaggregate the data to find it trustworthy and appropriate; only then could teachers rely on the findings as influential for instructional decision making (Namvar & Intezari, 2021). The process of wise data-driven decision-making (WD3M) echoed the need for teachers to apply their psychological ability to data analysis (Namvar & Intezari, 2021).

Data Intersections. Data analyzation practices were reported less frequently than data collection; however, the weakest of all the data analyzation practices was the intersection of two, three, or four types of ELD data. Only 21% of ELD teachers reported analyzing the intersection of two data types, 23% intersected three, and 25% intersected four. Furthermore, only two ELD teachers (5%) described intersecting data in the open-ended responses. The emphasis on more data variety is substantial in the literature (Finn, 2022; Vail, 2022; Wiseman & Bell, 2021). Vail

(2022) called for a richer spectrum of data, especially post-Covid 19. Fitzpatrick and Margolin (2004) reported:

> Education leaders often lack formal training in data analysis. They may suffer information overload when they attempt to draw conclusions from dozens of variables. To remedy the situation, educators need a process for data-driven decision making that helps them focus on the essential pieces of information to identify priority areas and select realistic goals. (p. 1)

The present findings are consistent with the literature; data collection practices are amply available and occurring, but data analyzation practices are not. Some possible explanations are the lack of data analysis training (Fitzpatrick & Margolin, 2004) or, as the study participants described, the lack of time, resources, or LEA and SEA directives. After collecting the data, the goal of using data is to analyze the raw data and turn the data into usable knowledge. The present study and the literature are synchronous regarding the need for not only developing teachers' data analyzation skills (Fitzpatrick & Margolin, 2004), but also, improving the data variety being intersected in these analyses for a better scope of knowledge (Finn, 2022; Mandinach & Schildkamp, 2021a).

Conclusion Two: Lack of Data Uniformity

ESSA has yet to create uniformity around data practices (Skinner, 2019; Vail, 2022), especially with ELD programs (Wiseman & Bell, 2021; Garver, 2022). While the ELD educators in the present study demonstrated some data usage and perceived importance, the need for uniformity and consistency between participants was evident.

Additionally, data variety might be indicative of increased data usage and importance. The rigidness of NCLB was not without faults (Garver, 2022), and the flexibility of ESSA is possibly influencing an unintended depletion of data (Vail, 2022; Finn, 2022). Kurz et al. (2018) called the lack of data, “the missing link” (p. 1) between knowledge and quality educational decisions. More data variety might be a compromise encompassing the benefits of both systems. Some options of data variety within accountability, such as the data categories analyzed in the present study (outcome data, instructional process data, and perceptual data), but these are not the only data metrics that could uphold an accountability system. In the open-ended responses written by the ELD teachers, there was a call for more varied uses of data and data types in ELD. Hyslop noted, “There are a lot of things that states can do to improve their data and be thinking about measures in different ways so that we’re getting a fuller picture than we have now of schools” (as cited by Vail, 2022, p. 35).

According to the qualitative responses in expansion question one, data collection and analyzation were important and valuable for informing instruction according to the descriptions of 19 participants (44%). Beneficial of the qualitative research approach, the distinction could be made between the 46 data supportive remarks, such as informing instruction, and 22 data negligent remarks in the responses to the first expansion question. Seven data negligent remarks referenced lack of data use and seven referenced lack of data importance. Six participants also reported a lack of data-driven identity, five referred to a lack of guidance from the district and state, and four mentioned a lack of time and resources. Consistent with the present research, Stecker et al. (2005) found that without knowledge and efficacy in data practices, teachers were frustrated, struggling, challenged, lacked time and strategy for data use, and were reluctant to collect data. Dunn et al. (2013) connected these feelings of negative perceptions, concern, and frustration to data anxiety. Data anxiety has been shown to decrease through the use of several practices, such as data professional learning (Dunn et al., 2013), professional learning communities (Schnellert, 2021), and cognitive disfluency (Duhigg, 2016).

The perceptual data all demonstrated a low, positive correlation when measuring the relationship between educator age and the individual data collection importance ratings. Furthermore, the correlation between the data collection and analyzation type and the perceived importance of that data type, also showed a moderate, positive correlation: perception of parents (r_{pb} = 0.71) and perception of students (r_{pb} = 0.71). These correlations were amongst the most significant in the study, but the relationship was not supported in the open-ended or data analysis responses. Fitzpatrick and Margolin (2004) explained that perceptual data could create a scale for the quality of experience. These reflections are more subjective but provide more depth due to the more qualitative nature of the responses.

Other types of data collection that ELD teachers reported using the most frequently were assessments developed by teachers (88%), assessments developed by the district (84%), attendance (84%), documenting instructional strategies (81%), and servicing time (81%). These findings demonstrate that teachers in ELD are collecting data, or as Young et al. (2018) described data, the arsenal of raw material which derives meaning. When the data collection practices were broken into categories: outcome data (performance data and demographic data), instructional process data, and perceptual data, teachers reported using instructional process data most frequently (79%). This finding is in slight opposition to the findings of previous research literature denoting outcome data as the most prevalent and lone outlier for data collection enacted (Wiseman & Bell, 2021; Fowler & Brown, 2018). Summative, standardized performance data was reported by 77% of teacher respondents. Demographic data (i.e., graduation rates and retention rates) was reported to be used the least by surveyed teachers (34%). However, this finding could be influenced by many participants (77%) educating elementary or middle school students. When further analyzed, this statistic was greatly influenced by the grades the ELD teacher taught. In the present study, 100% of ELD teachers from high school levels reported collecting both retention rate and graduation rate data. The mean perceived importance ranking of retention and graduation rates was 4.66 out of 5 for the high school teachers who participated in the survey. Therefore, this demographic finding cannot suggest the whole group of participants.

A limitation of this study was the lack of quantity and quality measures incorporated into the survey instrument. The data findings disaggregated through question one presented the first indication of the uniformity concern with the language used and practices considered when reporting on data collection and analysis in ELD. Of the open-ended responses, only 16% of participants (*n* = 7) referenced documenting with charts, graphs, reports, or spreadsheets, compared to the 81% of participants who affirmed to *charting the progress of individual students* on the quantitative survey question. Heiskanen et al. (2019) found 87% of educational records lacking detail, imprecise, vague, incoherent, or nonexistent. Most educational records fell into four categories: missing, repetitious, disorganized, and explicit (Heiskanen et al., 2019). In the present study, though 35 ELD educators reported collecting instructional servicing strategies and instructional servicing time, after coding the open-end responses, the researcher wondered whether the quality of each teacher's data practices were comparable. Based on the contradiction report presented in the limitations section and the data collection practices described in the open-ended self-reflection, the researcher is compelled to celebrate the frequency distribution data conservatively. Furthermore, research literature demonstrated a lack of empirical, publicly available, systematically collected, disaggregated data, which makes it impossible to conduct data analyses universally (Wiseman & Bell, 2021; Fowler & Brown, 2018). The present research does not support or deny this assertion, but rather continues to demonstrate the inconsistency of the data practices in ELD.

In addition to the moderate correlation between perceived importance and the collection of perceptual data, moderate, positive correlations were calculated between the perceived importance of instructional model ($r_{pb} = 0.67$), instructional time ($r_{pb} = 0.67$), behavior/discipline ($r_{pb} = 0.60$), student portfolios ($r_{pb} = 0.57$), standardized assessments ($r_{pb} = 0.55$), classroom assessments ($r_{pb} = 0.53$), and attendance in ELD groups ($r_{pb} = 0.51$). The types of data teachers reported analyzing had a moderate correlation with the teachers' perceived importance in identifying trends and patterns over time ($r_{pb} = 0.59$) and charting the progress of individual students ($r_{pb} = 0.59$). These correlations intrigued the researcher because they failed to demonstrate uniformity while identifying a connection between data practices and perceived importance. If a data practice was perceived as useful by the ELD educator, then that data practice was more likely to be enacted. However, the only data practice uniformly used by ELD educators was the WIDA ACCESS. Of all the other categories, data collection and analyzation lacked uniformity across ELD programs but showed a relationship with the perceived importance of the educator.

Conclusion Three: The Influence of ESSA Regulations

While age and tenure did not impact ELD teacher DDDM, the intersectionality of DDDM and teacher tenure (and age) might reveal a broader phenomenon. Both null hypotheses for the present study were rejected, failing to denote that a statistically significant relationship existed between an educator's years of experience teaching in an English language development program and the types of data collected and analyzed to modify instruction and the perceived importance of data collection and analyzation to modify instruction. Therefore, based on the nonsignificant correlational relationship, whether ELD teacher tenure does or does not affect data collection and analyzation practices or ELD teacher perceived importance of DDDM cannot be suggested. These findings were similar to those of Cronin (2001) and Zigmund (2020), who completed similar research studies with administrators and mainstream teachers, respectively. Nevertheless, these lesser and nonsignificant correlations could still impact our understanding of the current DDDM practices of ELD educators.

A possible explanation for the lack of correlation between the length of ELD teaching experience and data usage could relate to the inception of the ESSA and Title III. The No Child Left Behind Act (NCLB) (2002) was reauthorized as the Every Student Succeeds Act (ESSA) in 2015 (Skinner, 2019). NCLB accountability systems focused on achievement, graduation rates, and metrics (Vail, 2022). Under ESSA, states were granted flexibility in developing their accountability systems (Skinner, 2019). However, Vail (2022) contended that many states took advantage of this flexibility and failed to show improvement in 2020 analyses produced by All4Ed, a non-profit educational equity agency. In the present study, 40% of the ELD educators have only taught during the ESSA accountability era (<8 years). The drastic change between the more rigid NCLB and ESSA's ample flexibility and minimal data focus likely influenced the need for more clarity and uniformity of self-reported data practices for ELD teachers, evident in the statistical findings in this study.

Of all the statistical correlations of the present research, the data collection and analyzation type and the perceived importance of that data type had the strongest correlation. These findings suggest two possible explanations. The more a teacher uses a specific type of data collection or analyzation practice, the more importance the teacher will credit that practice.

Conversely, the opposite possibility is true. The more importance a teacher places on a data collection or analyzation practice, the more likely they will use that practice. Each of these suggestions could stem from different possible explanations. As discussed, ESSA has yet to emphasize data practices (Skinner, 2019; Vail, 2022), especially with ELD programs (Wiseman & Bell, 2021; Garver, 2022). The importance of national accountability systems (SEAs and LEAs) placed on data collection and analysis determined the likelihood educators will put on data use (Vail, 2022). Finn (2022) also validated the importance of an effective data system in educational systems and the reluctance of some educators who view data as the means to results-based accountability, which was described as "embarrassing, punitive, and a rejection of professionalism" (p. 13), and not a ripe environment for quality DDDM. Consistent with the present findings and research literature, more data emphasis and DDDM directives might be one of the answers to increasing the collection and analyzation of data, as well as the perceived importance of data.

Data emphasis is limited in ESSA guidelines, especially in Title III (Fowler & Brown, 2018). 40% of participants have only taught in ELD positions under the ESSA. In these past eight years, data usage has become less of a focus (Vail, 2022), which could influence the lack of importance placed on ELD data. The findings also suggest that older ELD educators collected and analyzed more data. Educator age was the only demographic covariant with a low, positive correlation to the perceived data collection importance score ($r_{pb} = .37$) and perceived data analysis importance score ($r_{pb} = .35$). These findings are consistent with the possible explanation that older teachers might have started their ELD teaching careers during the NCLB era and were influenced by the more rigid data practices.

Conclusion Four: More Professional Learning (PL) on DDDM

While PL experiences were not a primary focus of this study, the researcher found it interesting to compare the data collection practices of those who completed more PL experiences to those who completed fewer. A consistent limitation of the research study broadly, no distinction was made between the quantity and quality of the PL experiences beyond the basics of the experience occurrence. About half of the participants (56%) reported experiencing 0-1 PL experience on data collection and analyzation (n = 24), and 40% of participants explicitly reported no data-focused PL experiences. Unsurprisingly, PL on data collection was reported as the most frequent PL experience (n = 19). The PL experiences aligned with the frequency distribution indicating data collection practices as a more regular practice for ELD teachers. ELD teachers reported collecting more ELD data and more PL experience in data collection, adding to the literature on the positive connection between PL experiences and DDDM practices.

The research found a low, positive correlation existed between more PL and *charting progress of individual students* (r_{pb} = .40) and *posing questions or hypotheses and analyzing data* (r_{pb} = .42). These findings suggest a slight connection between educators' PL experiences and some of the data analyzation practices. Dodman et al. (2023) also found a similar occurrence in their research on combining data and equity literacy to promote a DDDM model called Data Use for Equity. A year-long PL experience primarily focused on developing the data and equity literacy skills necessary for Data Use for Equity (Dodman et al., 2023). According to Dodman et al. (2023), the most effective PL in data use for equity was ongoing and included teachers and administrators. The participant outcomes included increased agency, benefits to perceptions of equity and data, and a broader perception of multicultural capacities. The present findings and literature suggest that more professional development on data usage could influence more data collection and analyzation for all teachers, even ELD teachers.

As established through the findings, data analysis practices were present less frequently in the ELD teacher practices, as accounted by their survey and open-ended responses. The most frequent data analysis practice described in the open-ended responses was collaborating to discuss data (30%) (*n* = 13). Collaboration can be an effective PL experience. Boudett (2015) described Harvard School of Education's Data Wise as a DDDM procedure to organize and bring coherence to using data to improve education. One of the foundational habits of the eight-step DDDM process is intentional collaboration (Boudett et al., 2015). Dodman et al. (2023) also echoed the power of collaboration in the *Data Use of Equit*y program, describing how stakeholders from all levels got involved in data discussions. In the open-ended responses, 15 ELD educators from the present study also affirmed attending a Professional Learning Community on DDDM and multiple open-ended responses identified the influence these PL groups had on their quality data practices and overall PL experiences. Unfortunately, the Professional Learning Community on DDDM described by participants was not explicitly ELD focused, which could deter from the specificity of ELD data practices needed in the sub-divisional field of education (Hall-Mills et al., 2022).

These findings suggest a slight connection between educators' PL experiences and some of the data analyzation practices. Of the PL experiences described in the open-ended remarks, about one-fourth of participants (23%) reported receiving PL experiences in WIDA PL courses (n = 10), district PL communities (16%) (*n* = 7), and personal data-focused research (16%) (*n* = 7). Three participants referenced the need for ELD-specific data collection practices, like the other educators across the field, articulating the lack of training and more specific PD opportunities specific to their role and responsibility (Hall-Mills et al., 2022). Dunn et al. (2013) supported PL as an effective strategy for lessening feelings of concern around data, including anxiety, negative perceptions, and frustration. An increase in effective PL experiences, specific to ELD teachers' data collection and analyzation practices, could effectively solve data concerns and increase teacher data efficacy. The success and effectiveness of a PL experience in improving teaching practices can also be influenced by the program design (Kennedy, 2016), collaboration grouping (Schneller, 2021), ideas for enactment (Kennedy, 2016), and specificity of the practices to the participants' field of work (Hall-Mills et al., 2022). Participants from multiple research studies accredited PL for its positive impact on the adoption, confidence, and efficacy of new initiatives (Hall-Mills et al., 2022; Dodman et al., 2023).

Data efficacy is a primary component of learning success and could be a precursor to data usage and increased perceived importance (Dunn et al., 2013). Like other types of efficacies, data efficacy is developed over time, through positive, affirming experiences (Bandura, 1997) and shows a strong connection to PL experiences on data practices (Gesel et al., 2021). Gesel et al. (2022) meta-analysis showed that PL experiences on data knowledge significantly affected teacher outcomes ($g = .57$). The findings demonstrated the importance of developing data self-efficacy because teachers' beliefs about data abilities were significantly intertwined with knowledge, skills, and student outcomes (Gesel et al., 2021). PL experiences were lacking prevalence in the present research findings, which could explain the lack of data practices, data inconsistency, and lack of uniformity across the field of ELD.

Scholar Contribution

A contribution to scholarship is the act of providing new knowledge to the wealth of literature already woven into what is known. Boyer (1990) provided a more encompassing frame of scholarship, which included discovery, integration, application, teaching, and engagement. Through this present study, the researcher completed the discovery of investigating the new knowledge and pursuing this research. *Integration* was achieved in Section Three through the analysis of the literature on the topic of data collection and ELD. The *application* can be found in Section Four, as the findings were synthesized with the previous literature. The Scholar Contribution section will provide plans for the *teaching* through disseminating the present research findings in the target research journal. The Practitioner Contribution section provides the plan for *engagement* as it attempts to solve the lack of data uniformity in ELD programs.

Target Journal and Rationale

Where is the data? A Quantitative Study on the Lack of Data Collection and Analyzation in English Language Instruction, a journal manuscript, was prepared based on the present findings and using the guidelines for the journal, The TESOL Quarterly (TQ) (TESOL Quarterly, 2023). The TESOL Quarterly publishes four issues annually in February, May, August, and November. Manuscripts of research studies, literature reviews, or book reviews undergoing a double-blind peer review process. The researcher chose this journal based on the connection to the studied topic of ELD, the acceptance of research articles, and the widespread popularity of TESOL Quarterly in the field.

The article represents the researcher's contribution to literature, showing how this research applied to the researcher's organization and has been prepared for an external audience. This publication will allow for the widespread distribution of the findings of this correlational study and set a foundation of validity for the need for ELD data and analyzation in New Hampshire. The manuscript was prepared following the guidelines for TESOL Quarterly Journal.

Practitioner Contribution

Through this scholarly journey, the researcher developed an ELD data collection, analyzation, and reporting instrument based on early perceptions and anecdotal evidence. The data collection mode and model concept began in 2020, but the DOKed software tool will complete the next phase of development based on these research findings. The researcher determined the need for more data practice uniformity and better analyzation practices for ELD teachers in New Hampshire. The updates to the data collection and analyzation instrument better supported teachers' needs for uniformity, analyzation best practices, and collaborative DDDM PL experiences.

DOKed Data Collection & Reporting

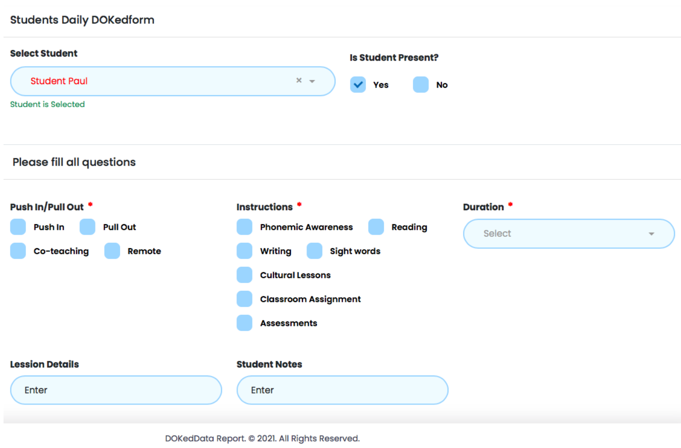
DOKed is a comprehensive data collection and reporting software for ELD designed to capture the additive instructional interventions provided to ELLs by their ELD teachers. The software provides a technological and systematic mode and method for uniform documentation of ELD servicing blocks with students based on Federal ESSA compliance. The software intends to provide educators with an easy-to-use, comprehensible system of documenting and monitoring student attendance, progress, and guide future instruction. Based on the present findings, data analysis needs to be improved, for which DOKed provides a solution. ELD teachers' data collection becomes more straightforward and uniform, and data analytics occur instantaneously and seamlessly to provide teachers with a data dashboard, including charts and reports to analytics to better guide instructional practices.

DOKed was designed according to the strict requirements for all electronic and physical forms, including students' or teachers' personally identifiable data described by The State of New Hampshire Minimum Standards for Privacy and Security of Student and Employee Data report (n.d.). The DOKed software system was created to meet these standards for ELD data collection and reporting, and offer a systematic, electronic data collection method alternative to traditional methods or the absence of a method. Individualized profiles were accounted for within the software to be a highly accepted solution and follow the recommendation of Kurilovas (2016). The system was created with features cognizant of ease, usefulness, and timeliness for ELD teachers to capture outcome, perceptual, and instructional process data. The charts and reports on the analytics dashboard are intentionally comprehensible and meaningful visuals of the data for teachers and administrators. The development of DOKed occurred in the context of ELD where the lack and need for documenting and recording serving quantity, context, and quality were evident. The design further reflects the findings disaggregated from the present research.

Within the software, teachers can utilize a daily *DOKit!* Form for each student receiving services that day. The *DOKit!* Form, shown in Figure 13, includes documentation for attendance, instructional model, instructional content, duration, lesson details, and perceptual notes reflected by the teacher (or other teachers), parents, or the student.

Figure 13

DOKed DOKit! Form



(Leone, 2021)

Based on the daily, uniform instructional process data collected by this daily form entry, reports can be generated by the teacher, school administrators, district administrators, and DOE. School administrators can see a bird's eye view of how educators are servicing students in a constant and standardized way. Outcome data is readily available (Wiseman & Bell, 2021; Garver, 2022), but this could be considered a gap in the current version of the DOKed software. The research findings and literature support the call for increased data uniformity and the merger of multiple, varied data points for quality DDDM (Vail, 2022; Finn, 2022). DOKed will offer just that. Furthermore, district and DOE leaders can access complete reports on district ELD data to verify compliance, guide decisions, and supplement grant writing.

Influenced by the literature support and present findings on PL experiences in data collection and analyzation, the researcher accompanied DOKed software with a DDDM for Equity PL experience. The present study found that ELD teachers received infrequent PL experiences on data collection and analyzation. PL experiences have been shown to increase data literacy (Dodman et al., 2023), data efficacy (Dunn et al., 2013), and have a positive influence on change action (Hall-Mills et al., 2022). The DOKed PL experience will draw from multiple successful data programs, including DDDM (Mandinach et al., 2006), Data Wise (Boudett et al., 2015), and Data Use for Equity (Dodman et al., 2023). Using PL best practices, the DOKed PL experiences will utilize the practices derived from change, organizational, and learning theories in guiding employees through the transformation and innovation of their data practices. As Schnellert (2021) and Dodman et al. (2023) encouraged, the power of collaborative learning networks will be engaged as ELD teaching teams will participate in cooperative learning with colleagues and administration. These PL experiences will be highly focused on ELD-specific data collection and analyzation. The DOKed PL experiences is outlined further in Appendix H.

Plan for Dissemination

In addition to an article publication and practitioner data software solution, the researcher will simultaneously work with the New Hampshire Department of Education to offer DOKed software to individual teachers and districts. The researcher presented initial data concerns at the Statewide EL Educators’ Community of Practice meeting in October 2021 and found this group favorable. The researcher would like to utilize this group again to invite teachers to become more involved with piloting the ELD data software solution based on these findings. NHED will be able to provide valuable networking opportunities to work with districts that are ripe for an ELD data incentive. The high-incident district officials who endorsed the present study also expressed interest in further data collection and analyzation solutions, along with the findings of this research. The research will request an opportunity to present the conclusions and DOKed software with each of the endorsing school districts’ administrative teams.

In the past, the researcher has presented action research findings through multiple platforms, including the National TESOL conference, the Northern New England TESOL conference, Ellevation, PBLworks, NHPR, Smartbrief, and multiple other news and podcast sources. The researcher will apply to present at the 2024 TESOL conference and pursue presentation opportunities with the news and podcast sites with which the researcher has previously worked.

SECTION SIX

RESEARCHER REFLECTION

This study explores ELD data collection and analyzation practices in New Hampshire. The types of data used regularly were identified and rated by teacher-perceived importance. Calculations were analyzed for correlational relationships between the types of data used, the teacher-perceived importance of these data types, and the tenure of an educator's teaching career in ELD. Section Six is the researcher's reflection on the dissertation process as a practitioner, an educational leader, and a scholar. The remainder of Section Six will be the researcher's first-person accounts of the transformational process.

Practitioner Reflection

When I began to wonder about the scope of DDDM practices utilized by ELD teachers in New Hampshire in 2020. Simultaneously in early 2020, the Black Lives Matter campaign greatly swept the nation. People of all races took to the streets in advocacy for the rights of colored friends, neighbors, family members, and even strangers. The ring of voices advocating for people of minorities and colors to receive better medical care, workplace equality, and fairer court rulings is substantial, but I was surprised about the absence of educational advocacy for our newest minority community members. In 2022, students with limited English proficiency continue to be among the most marginalized educational subgroups (Garver, 2022).

I began to recognize that my LEA and ELD sphere of influence collected very little data, and I wondered how widespread the problem was. I questioned whether effective data collection methods and practices existed in ELD, how data *should* be collected and used, and if directives existed from the ESSA: Title III, or Office of Bilingual Education and World Language (OBEWL). The semantics of the word, *should*, implies advice or recommendation.

As I began this dissertation journey, my investigation revealed that data guidance or recommendation from ESSA and OBEWL did not exist, nor was data frequently collected by ELD educators in New Hampshire. This is a grave and inequitable misfortune for the marginalized subgroup of ELLs. The injustice reflects the national trend of subpar education of our refugee, immigrant, and black and indigenous people of color (BIPOC) communities (Fowler & Brown, 2018; Garver, 2022), despite the federal provisions (Garver, 2022) and ELD best practices suggested internationally (TESOL, 2023c)

In 2020, I began to ask representatives from the agencies involved with educating ELLs in my LEA how they collect and use data. The answers were shrugs, unreturned emails and phone calls, and confusion that data should be collected and used in the field. I went as far as to ask two English language development database organizations to consider creating a system in readily used ELD databases. The research findings only added to my frustration and determination to find data best practices, and I needed a strategy that would allow and assist my data collection and usage for ELD students on my caseload, in my school.

Through the dissertation journey and as I investigated DDDM for ELD, I was surprised at the considerable resistance I faced. I was told by colleagues, administrators, and officials at the SEA that data did not matter in more ways than I can count. I had difficulty finding school districts and ELD teachers to participate. Overall, the culture around DDDM in ELD was unwelcoming. Yet, I knew the power of implementing quality data, so I kept pursuing the topic in an attempt to reveal the enacted DDDM practices. The findings from this study were surprising, but they reiterate for me the disconnect between data collection quality and quantity discourse in ELD. In the present study, many of the participants' responses on data practices contradicted the open-ended responses, which demonstrated the inconsistency of data understanding, data practice expectation, and lack of uniformity around DDDM in ELD.

These findings have helped refine my understanding of New Hampshire ELD data collection and analyzation. I have used the statistical findings and literature to design and refine DOKed, a mode and method for data collection and analysis that allows for quick data collection, impactful analyzation, and production of reports to disseminate the data knowledge. I have shared these strategies in my district and state as a practitioner. Some ELD educators and administrators have found data oppressive and worried that data would encourage too much accountability and result-driven practices. Other ELD teachers and administrators have met the data collection and analyzation opportunity with excitement and a desire to use the system to improve student guidance and instruction.

Educational Leader Reflection

As an educational leader, equity is extremely important. The lack of data collection and analyzation practices in my own LEA is an offense against the equity of our ELD systems. There are limited predictors of school achievement for students who are culturally and linguistically diverse (Dodson et al., 2021; Fowler & Brown, 2018), which highlights the need for increased educational equity (Adams, 1963). Adams (1963) described equity in terms of economics and business, but the theory has been heavily adopted by the educational field. Simply, equity is a fair exchange centered around relative justice (Adams, 1963). Equity dissonance for multilingual and culturally diverse students begins when they arrive and are challenged to learn in a language they do not yet understand. English language acquisition experts advise that it takes a student three to five years to acquire conversational English, and five to seven years to acquire academic English (Cummins, 1991). ELLs start their educational journey with a dissonance of equity. Brown (2018) explained that "the more inequity one feels, the more distress one feels as well" (p. 20). As an educational leader, I advocate against this distress by striving for more equity.

Ensuring equity for all students is a challenge facing our American educational system. I sought this dissertation study to contribute to bringing more educational equity to the school system for racial-ethnic student subgroups. While DDDM is primarily focused on assessment scores, using other formative data points from daily instructional tracking actualizes the educational status of marginalized students and will create a deeper sense of educational equity.

Equity theory highlights why some of the injustices continue and educational leaders can use equity theory to develop accountability systems for educators and schools and to create more just systems (Fowler & Brown, 2018). Fowler and Brown (2018) described how a lack of equity could impact school and student relationships. "The student picks up on cues of differential treatment based on marginalized group membership and adjusts behaviors to restore equity related to the perceived injustice. Children can also read in these cues that their abilities are not valued in the school's social setting" (p. 22). Hence, additive instructional services can support or deter the social and emotional foundations of ELLs in educational settings.

The racial-ethnic achievement gap is paramount to the ELD program dilemma. While achievement data does provide a glimpse at a portion of the problem, it does not portray the full picture or solution. Rowan and Correnti (2004) established that even with research on the impactful elements of the educational environment, efforts for widespread adoption showed limited success, and student achievement had not improved. There have been widespread efforts to identify the evidence-based practices most likely to increase academic achievement in the broad field of education (Hattie, 2017; U.S. Department of Ed., n.d.).

This study joins the emerging literature to disseminate the data and findings on best practices for achieving more equitable instruction. What Works Clearinghouse (WWC) is an example of a meta-analysis attempting to provide evidence of the effectiveness of educational practices which create more equity in education. WWC reviewers evaluate studies based on published quality indicators and summarize the findings to determine the best ways to bridge the achievement gap through equitable and effective programs, policies, and practices. However, the gap still exists of best practices for data collection and analyzation with uniformity and intention to bridge the racial-ethnic achievement gap. When we collect and analyze ELD data, we address the racial-ethnic achievement gap. With DDDM's data, information, and knowledge, better decisions could be made regarding policy, program, and pedagogy, which impact student success and are grounded in facts. As an educational leader, I advocate for solutions that create ELL equity.

Scholar Reflection

As a scholar, I have developed the knowledge and skills to explore a topic and present the findings. This occurred in two distinct ways. First, I had to examine my biases and challenge my assumptions about what I thought data practices looked like in ELD. And second, I refined my ability to "stand on the shoulders of giants" (Newton, 1675), a phrase that refers to the relationship between novice scholars like myself, and the giants as the scholars and scholarly literature that has come before.

As a scholar, I am dedicated to my research and investigation into the problem of practice I have identified, looking into the ELD and ESSA Title III policies and evaluating their effectiveness. This passion and dedication can lead to biases. Over the process of completing this research study, I have had to evaluate my ingrained view of how ELD was functioning. My biggest bias was a predetermined opinion of how and if data was being collected in ELD. Based on my ELD teaching experience, my bias was that ELD did not collect data and did not want to collect data. Surprisingly, ELD teachers did report the collection of data. I found that ELD data collection lacked uniformity and consistency, and data analysis occurred less frequently and in fewer ways when compared to data collection.

In Section One, I provided a list of assumptions I identified for the present research. The assumptions I held included:

- Teachers need a better system of servicing data collection and analyzation
- ELD educators lack data efficacy
- Data reports should be easy to access and useful
- Data is necessary for better, quality instruction in Title III and other ELD servicing programs
- Record keeping for daily instructional opportunities is lacking in the field of education, especially in educational subgroups
- Technology is the future of data collection

Through my research, I had to leave space for the possibility that research did not support these assumptions. By assessing and recognizing my prior biases and assumptions before the research process, I could analyze the data findings unbiasedly and without assumptions.

Examining literature and federal ELD policy reports, I became very cognizant of the need to rely on the 'giants' (Newton, 1675). I pursued scholarly conversations with researchers and content experts whose work resembled my current questions and insights. One of the researchers who helped shape my thinking was Kurz (2018), who recognized the data gap and lack of data in special education. Kurz developed the Opportunities to Learn (OTL) framework to track the instructional trifecta in the classroom. The core indices of OTL are instructional time, content, and quality of instruction (Kurz et al., 2014). Regular collection of OTL data could be disaggregated and used to make quality educational decisions. Through multiple conversations with Kurtz in 2021, I recognized OTL data as a highly valuable component of the instructional data process.

My development into a better practitioner, educational leader, and scholar could be connected to the OLT framework. Through multiple studies, Kurz et al. found that student achievement can be estimated by analyzing learning data through the OTL lens (Kurz et al., 2010; Kurz et al., 2014; Kurz et al., 2015). Most national accountability systems in the United States assume that OTL is occurring for all students (Kurz et al., 2014). OLT is not one size fits all in the classroom; the framework creates equitable learning opportunities. Kurz et al. (2010) emphasized the need to differentiate the indices based on each student's intended curriculum. As a scholar with data literacy, I am encouraged to operationalize the practice of collecting indices of OTL: time, content, and quality. A scholar has a role of continued inquiry. I wondered how better insight into the enacted OTL for ELLs would assist in the data snapshot that would benefit the educational system.

ESSA: Title III ensures ELLs access the academic standards that guide the general curriculum (Skinner, 2019). Despite the significant achievement gap for ELLs (Fowler & Brown, 2018), researchers have failed to draw empirical conclusions. When discussing a similar gap in special education, Kurz et al. (2014) concluded that student achievement can be estimated. This failure "is partly due to the conceptual and methodological challenges of operationalizing the concept of OTL and assessing OTL via measures that can account for teachers' instructional provisions to the overall class and to individual students" (Kurz et al., 2014, p. 24). Through this research, I explored what data is being collected and analyzed in ELD; however, the findings have only led to many more scholarly questions.

The conceptualization of OTL has provided a reliable, relevant, and applicable framework for the educational system to be more equitable, aligned, and empirically standardized by the time, content, and quality indexes (Kurz, 2018; Kurz et al., 2014). After reviewing the intersectionality of ELD data practices, DDDM and OTL, documentation of the scope and sequence of quality instruction becomes necessary for providing evidence for the teacher's effect on learning and achievement (Kurz, 2018; Metcalf, 2012). Without measurement data, progress monitoring cannot exist. Research has provided the why for OTL; however, there still needs to be an index of the what and how of the instructional characteristics currently occurring in ELD. Furthermore, there is a complete omission of the degree to which the characteristics are presently implemented (Kurz, 2018). As a scholar, I am dedicated to continuing to pursue these answers.

Implications for the Future

Based on the findings from the present study, the researcher recommends three future focuses of investigation; (a) replicate the research in other states, (b) explore the data usage of ELD teachers with criteria of quantity and quality indicators, and (c) investigate the influence of federal ELD programming on ELD data collection and analyzation practice. Additionally, future research could explore how effective DOKed Data Software can positively influence Data for Equity practices and student achievement.

ESSA offers states ample flexibility in their accountability plans (Skinner, 2019), making the results from this study set in New Hampshire difficult to generalize across states. With the insight into the data collection and analyzation discovered in this research, future research could focus on how other states collect and analyze data in their ELD programs. The findings from this future research concept could weave a clearer picture of ELD on a broader or national level.

The findings from the present study indicate that ELD data collection and analysis in New Hampshire could use more uniformity. ELD teacher participants in this study were able to respond on a fundamental level about their involvement with certain data practices. However, the quantity and quality of these practices are still unknown. Future research could unpack the enacted data practices in extensively more detail. While this study provided a snapshot of the data practice occurring, for the participant sample, future research exploring the precision of these data practices would focus the snapshot.

This research touched on the influence of ESSA: Title III influence and guidelines, but future research could look specifically at the influence of these programs on ELD data practices. Some states solely use Title I funding or other means to resource their ELD programs; others do not collect grants (Boyle et al., 2010). The literature review and study revealed the need for broad reform and clarity of policy and accountability for ELD programs.

Lastly, the researcher recommends that software developers and innovation teams conduct a user preference assessment and system usability evaluation for suitability, acceptance, and use of IT applications of current and future data collection systems for ELD programs, including DOKed software using an adequate participant sample. If ELD data solutions were available, data collection and analysis would present fewer barriers and provide more synchronous data practices for ELD educators. However, innovations like a technological approach to data collection might be difficult to implement without educator support (Kurilovas, 2016). Reducing computer anxiety among users before introducing new electronic data solutions is vital to acceptance (Parr et al., 2004). Progressive solutions are a way of the future, but more research devoted to implementing ELD-specific technological data tools would be beneficial.

Conclusion

Aside from low achievement scores and language proficiency scores, little was known from the literature regarding the education of ELD students due to the lack of additive instructional servicing data available for this underserved group of students (Fowler & Brown, 2018). This quantitative correlational survey study explored the importance of data collection and analyzation practices for ELD educators in New Hampshire through the lens of Mandinach et al.'s (2006) data-driven decision-making (DDDM) framework. The framework flows raw data through three phases: collection, information, and knowledge (Mandinach et al., 2006). Data-driven decision-making is often recognized for its importance and value. However, more research is needed to describe the extent to which data collection and analysis are implemented in ESOL additive instructional settings. The study explored the strength of the association between ELD teaching experience and data-driven decision-making using *A Survey to Assess Data Use in Educational Decision-Making* (Cronin, 2001). Forty-three teacher participants from three New Hampshire school districts with ELLs completed the survey to glean an understanding of the types of data teachers use to modify instructional practices, types of data analysis techniques teachers use to modify instructional practices and teachers' perceived importance of data collection and analyzation.

The findings from this study explored the relationship between ELD educators' experience teaching and data collection and analyzation through the lens of the DDDM framework. Consistent with the literature on the prevalence of standardized assessment data in ELD, WIDA data was used and analyzed the most frequently. Additionally, data collection occurred more frequently than data analyzation for the ELD educators. There was a low to moderate, positive correlational relationship between the data types used and the perceived importance reported by the ELD teacher participants, suggesting that the more important an ELD teacher perceived a data practice, the more likely they were to enact that type of data in their daily practices. According to Kurilovas (2020), users must perceive the usefulness of an incentive before they fully buy in, and Dunn et al. (2013) credited data efficacy to the scale of confidence with data practice. The ELD teacher participants also reported minimal exposure to PL experiences, especially PL experiences on ELD-specific topics.

The compilation of the present findings and research literature provides a cross-sectional, snapshot of the enacted data practices of ELD educators in New Hampshire and evidence of the need for richer data on student subgroups (Wiseman & Bell, 2021; Fowler & Brown, 2018; Garver, 2022). With more data literacy, educators and administrators can (a) gain great insight by examining their current data collection and analyzation practices for ELLs in their educational care, (b) consider the findings of the present study in order to determine the importance of data collection and analyzation for ELD programs and use this to improve current practices and increase accountability, (c) consider creating a norm for quantity and quality of data collection and analyzation in their current practices. To reach this goal, future research on ELD data collection and analyzation across the United States, the uniformity of ELD data practices, and the influence of Federal ESSA: Title III programming, should be completed.

Hyslop suggested, “There are a lot of things that states can do to improve their data and be thinking about measures in different ways so that we’re getting a fuller picture than we have now of schools” (as cited by Vail, 2022, p. 35). Based on the findings from the present study, the research presented four conclusions. First, data collection practices are more frequently used than data analysis practices. Duhigg (2016) contended that data processed intentionally greatly impacted on teacher usefulness of the data, but Namvar and Intezari (2021) found that data analysis too often lacked explicitness. Second, ELD data uniformity and variety were missing. Similar to the findings of Vail (2022), Garver (2022), and Finn (2022), a teacher in the present study reported that their LEA and SEA failed to provide direction on DDDM. Third, the transition from NCLB to ESSA resulted in a data deficit. The increased flexibility has caused an even greater data gap (Vail, 2022), especially for student subgroups like ELLs (Fowler & Brown, 2018). Lastly, the final conclusion was that PL experiences were lacking. Literature proposed that by utilizing quality and specific PL experiences, ELD teachers would collect and analyze more data (Gesel et al., 2021; Kennedy, 2016), feel greater data efficacy (Dunn et al., 2013), and better use data and findings to inform instruction (Dodman et al., 2023). PL is a highly effective strategy for engaging data practices (Kennedy, 2016; Schnellert, 2021) and would likely have a positive effect if implemented with ELD educators in New Hampshire.

References

Ackoff, R. L. (1989). From data to wisdom. *Journal of Applied Systems Analysis, 16*, 3-9.

Adams, C. D. (2021). *Educators' perspectives of using G Suite for education with chromebooks: A narrative inquiry* (Order No. 28315374). ProQuest Dissertations & Theses Global. (2506330010). https://ezproxy.snhu.edu/login?qurl=https%3A%2F%2Fwww.proquest.com%2Fdissertations-theses%2Feducators-perspectives-using-g-suite-education%2Fdocview%2F2506330010%2Fse-2%3Faccountid%3D3783

Adams, J. S. (1963). Towards an understanding of inequity. *The Journal of Abnormal and Social Psychology, 675*, 422-436.

Agustina, M., & Purnawarman, P. (2020). Investigating learners' satisfaction utilizing Google Classroom as an online formative feedback tool. *2020 6th International Conference on Education and Technology (ICET), 2020 6th International Conference*, 26–31. https://doi-org.ezproxy.snhu.edu/10.1109/ICET51153.2020.9276616

Albashtawi, A. H., & Bataineh, K. B. A. (2020). The effectiveness of Google Classroom among EFL students in Jordan: An innovative teaching and learning online platform. *International Journal of Emerging Technologies in Learning*, *15*(11), 78–88. https://doi-org.ezproxy.snhu.edu/10.3991/ijet.v15i11.12865

Bandura, A. (1997). *Self-efficacy: The exercise of control*. Freeman.

Beecher, M., & Sweeny, S. M. (2008). Closing the achievement gap with curriculum enrichment and differentiation: One school's story. *Journal of Advanced Academics, 19*(3), 502–530. https://doi.org/10.4219/jaa-2008-815

Birman, B. D., & Tran, N. (2017). When worlds collide: Academic adjustment of Somali Bantu students with limited formal education in a U.S. elementary school. *International Journal of Intercultural Relations*, *60*, 132–144.

Bolman, L. & Deal, T. (2017). *Reframing organizations.* Jossey-Bass.

Boudett, K. P., City, E. A., & Murnane, R. J. (2015). *Data wise: A step-by-step guide to using assessment results to improve teaching and learning*. Harvard Education Press.

Boyer, E.L. (1990). *Scholarship reconsidered: Priorities of the professoriate*. Jossey-Bass.

Boyle, A., Taylor, J., Hurlburt, S., & Soga, K. (2010). Title III accountability: Behind the numbers. *ED Pubs: US Department of Education*. http://www.edpubs.gov.

Brown, B. (2018). *Dare to lead. Brave work. Tough conversations. Whole hearts.* Random House.

Buzhardt, J., Greenwood, C. R., Jia, F., Walker, D., Schneider, N., Larson, A. L., Valdovinos, M., & McConnell, S. R. (2020). Technology to guide data-driven intervention decisions: Effects on language growth of young children at risk for language delay. *Exceptional Children*, *87*(1), 74–91.

Cahalan, D. (1968). Correlates of respondent accuracy in the Denver Validity Survey. *The Public Opinion Quarterly*, *32*(4), 607–621.

California Department of Education. (2022). *English language proficiency assessments for California (ELPAC)*. California Department of Education. https://www.cde.ca.gov/ta/tg/ep/

Carney, T. (2020). FY21 Program assurances. *New Hampshire Department of Education.* https://www.education.nh.gov/sites/g/files/ehbemt326/files/inline-documents/2020-04/school-district-general-assurances-fy21.pdf

Carpenter, D. M. II. (2022). An analysis of the relationship between superintendent turnover and district performance. *Reclaiming Local Control through Superintendents, School Boards, and Community Activism*, 117-127.

Childs, M., McClintock, K., & Harris, G. E. (n.d.). Electronic versus data collection procedures in a behavioral program for children with autism. http://www.mobilethinking.com/dtm/downloads/Texas_Young_Autism_Project.pdf

Chu, H., & Fong, T. (2015). *Ninth grade newcomers in Fort Worth Independent School District: Comparisons to other English language learners*. WestEd.

Coulter, K. (2016). *Effectiveness of WIDA English language development standards meeting proficiency for English language learners* (Order No. 10243679). Available from ProQuest Dissertations & Theses Global. (1865652058). https://ezproxy.snhu.edu/login?qurl=https%3A%2F%2Fwww.proquest.com%2Fdissertations-theses%2Feffectiveness-wida-english-language-development%2Fdocview%2F1865652058%2Fse-2%3Faccountid%3D3783

Creswell, J. W. (2017). *Educational research: Planning, conducting, and evaluating quantitative and qualitative research (4th ed.)*. Pearson Education Inc.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches*. SAGE Publications, Inc.

Cronin, R. D. (2001). *A study to determine what student outcome data principals use for school improvement* (Order No. 3008114). ProQuest Dissertations & Theses Global. (230788665). https://ezproxy.snhu.edu/login?qurl=https%3A%2F%2Fwww.proquest.com%2Fdissertati ons-theses%2Fstudy-determine-what-student-outcome-data%2Fdocview%2F230788665%2Fse-2%3Faccountid%3D3783

Cummins, J. (1991). BICS and CALP: Clarifying the distinction. *ERIC*. https://files.eric.ed.gov/fulltext/ED438551.pdf.

DeMatthews, D. E., Reyes, P., Carrola, P., Edwards, W., James, L., & Texas Education Research Center. (2021). Novice principal burnout: Exploring secondary trauma, working conditions, and coping strategies in an urban district. Publication. *Texas Education Research Center*.

Dodman, S. L., Swalwell, K., DeMulder, E. K., View, J. L., & Stribling, S. M. (2021). Critical data-driven decision making: A conceptual model of data use for equity. *Teaching and Teacher Education*, *99*. https://doi-org.ezproxy.snhu.edu/10.1016/j.tate.2020.103272

Dodman, S. L., DeMulder, E. K., View, J. L., Stribling, S. M., & Brusseau, R. (2023). "I knew it was a problem before, but did I really?": Engaging teachers in data use for equity. *Journal of Educational Change*, 1-29.

Drucker, P. F. (1989). *The new realities: In government and politics/in economics and business/in society and world view*. Harper & Row.

Duff, P. (2014). Case study research on language learning and use. *Annual Review of Applied Linguistics, 34*, 233-255. doi:10.1017/S0267190514000051

Duhigg, C. (2016). *Smarter, faster, better: The transformative power of real productivity*. Random House.

Dunn, K. E., Airola, D. T., Lo, W.-J., & Garrison, M. (2013). Becoming data driven: The influence of teachers' sense of efficacy on concerns related to data-driven decision making. *The Journal of Experimental Education*, *81*(2), 222–241.

Education Law Center. (2022). *Rights of English language learners (ELL) & families with limited English proficiency*. Pennsylvania State Department of Education. https://www.elc-pa.org/wp-content/uploads/2015/05/Rights-of-ELLs-March-172014-Revised.pdf

Education Law Center. (2016). *Comments of education law center – PA to U.S. department of education's present regulations impacting educationally at risk students*. Pennsylvania State Department of Education. https://www.elc-pa.org/wp-content/uploads/2016/09/ELC-PAs-Comments-Re-present-ESSA-Regulations-Impacting-At-Risk-Student-1.pdf

Equal Educational Opportunities Act (EEOA), 20 U.S.C. § 1703 (1974). https://www.congress.gov/bill/93rd-congress/house-bill/40

English language development (ELD). (2019, June 12). Colorín Colorado. https://www.colorincolorado.org/glossary/english-language-development-eld

Estrada, P., Wang, H., & Farkas, T. (2020). Elementary English learner classroom composition and academic achievement: The role of classroom-level segregation, number of English proficiency levels, and opportunity to learn. *American Educational Research Journal*, *57*(4), 1791–1836.

Evans, M. (2015). *Data use for what and for whom?: A close look at the policies and teacher practices that shape data-driven decision making at an elementary school* (Order No. 3737642). ProQuest Dissertations & Theses Global. (1746695076). https://ezproxy.snhu.edu/login?qurl=https%3A%2F%2Fwww.proquest.com%2Fdissertations-theses%2Fdata-use-what-whom-close-look-at-policies-teacher%2Fdocview%2F1746695076%2Fse-2%3Faccountid%3D3783

Fairbairn, S. B., & Fox, J. (2009). Inclusive achievement testing for linguistically and culturally diverse test takers: Essential considerations for test developers and decision makers. *Educational Measurement: Issues and Practice*, *28*(1), 10–24. https://doi-org.ezproxy.snhu.edu/10.1111/j.1745-3992.2009.01133.

Fernando, P. R. (2020). Improving the quality of education system using data science technologies: Survey. *2020 5th International Conference on Innovative Technologies in Intelligent Systems and Industrial Applications (CITISIA), Innovative Technologies in Intelligent Systems and Industrial Applications (CITISIA)*, 1–6. https://doi-org.ezproxy.snhu.edu/10.1109/CITISIA50690.2020.9371793

Finn, C. E., Jr. (2022). School accountability: Yesterday, today, and tomorrow. *PHI DELTA KAPPAN*, *104*(3), 12–17. https://doi-org.ezproxy.snhu.edu/10.1177/00317217221136588

Fitzpatrick, M., & Margolin, J. (2004). Using data to guide school improvement. *North Central Regional Educational Laboratory*, 7, 1-14. https://files.eric.ed.gov/fulltext/ED518630.pdf

Fowler, D. J., & Brown, K. (2018). Data-driven decisions: Using equity theory to highlight implications for underserved students. *AASA Journal of Scholarship & Practice*, *14*(4), 18–28.

Fowler, F. (2014). *Survey research methods.* Applied Social Research Methods Series.

Frontline education acquires Accelify Solutions. (2019, October 3). *PR Newswire*. http://bi.gale.com.ezproxy.snhu.edu/global/article/GALE%7CA601576068?u=nhc_main

Fry, R. W. (2017). *Data-driven decision-making and the challenges facing Pennsylvania school administrators, compliance vs. conviction* (Order No. 10629049). ProQuest Dissertations & Theses Global. (1922666540). https://ezproxy.snhu.edu/login?qurl=https%3A%2F%2Fwww.proquest.com%2Fdissertati ons-theses%2Fdata-driven-decision-making-challenges-facing%2Fdocview%2F1922666540%2Fse-2%3Faccountid%3D3783

Garver, R. (2022). For some and for all: Subgroup entitlement policies and daily opportunity provision in segregated schools. *American Educational Research Journal,* 59(3), 574-609, DOI: 10.3102/00028312221079302

Gesel, S. A., LeJeune, L. M., Chow, J. C., Sinclair, A. C., & Lemons, C. J. (2021). A meta-analysis of the impact of professional development on teachers' knowledge, skill, and self-efficacy in data-based decision-making. *Journal of Learning Disabilities*, *54*(4), 269–283. https://doi-org.ezproxy.snhu.edu/10.1177/0022219420970196

Gordon, N., & Reber, S. (2015). The quest for a targeted and effective Title I ESEA: Challenges in designing and implementing fiscal compliance rule. *The Russell Sage Foundation Journal of the Social Sciences.* 1(3), 129-147; DOI:10.7758/RSF.2015.1.3.07

Hall-Mills, S., Johnson, L., Gross, M., Latham, D., & Everhart, N. (2022). Providing telepractice in schools during a pandemic: The experiences and perspectives of speech-language pathologists. *Language, Speech, and Hearing Services in Schools*, *53*(2), 290–306. https://doi.org/10.1044/2021_LSHSS-21-00023

Hatch, M. (2013). *Organizational theory*. Oxford University Press.

Heiskanen, N., Alasuutari, M., & Vehkakoski, T. (2019). Recording support measures in the sequential pedagogical documents of children with special educational needs. *Journal of Early Intervention*, *41*(4), 321–339. https://doi.org/10.1177/1053815119854997

Holfester, C. (2021). Teaching English as a second language. *Salem Press Encyclopedia*.

Ikemoto, G. S. & Marsh, J. A. (2007). Chapter 5: Cutting through the "data-driven" mantra: Different conceptions of data-driven decision making. *Yearbook of the National Society* *for the Study of Education*, *106*(1), 105–131. https://doi.org/10.1111/j.1744-7984.2007.00099.

Irizarry, J. G. (2009). Representin': Drawing from hip-hop and urban youth culture to inform teacher education. *Education and Urban Society*, *41*(4), 489–515.

Jimenez, K. (2022, October 11). *Latinos will make up nearly a third of US students in 2030. Will schools help them succeed?* USA Today. https://www.usatoday.com/in-depth/news/2022/10/11/latino-student-population-us-schools/10426950002/

Kurilovas, E. (2016). Evaluation of quality and personalisation of VR/AR/MR learning systems. *Behaviour & Information Technology, 35*(11), 998–1007.

Kurilovas, E. (2020). On data-driven decision-making for quality education. *Computers in Human Behavior*, *107*. https://doi-org.ezproxy.snhu.edu/10.1016/j.chb.2018.11.003

Kurz, A., Elliott, S. N., Wehby, J. H., & Smithson, J. L. (2010). Alignment of the intended, planned, and enacted curriculum in general and special education and its relation to student achievement. *The Journal of Special Education, 44*(3), 131–145. https://doi.org/10.1177/0022466909341196

Kurz, A. (2011). Access to what should be taught and will be tested: Students' opportunity to learn the intended curriculum. *Handbook of Accessible Achievement Tests for All Students*, 99–129. https://doi.org/10.1007/978-1-4419-9356-4_6

Kurz, A., Elliott, S. N., Kettler, R. J., & Yel, N. (2014). Assessing students' opportunity to learn the intended curriculum using an online teacher log: Initial validity evidence. *Educational Assessment*, *19*(3), 159–184.

Kurz, A., Elliott, S. N., & Roach, A. T. (2015). Addressing the missing instructional data problem. *Remedial & Special Education*, *36*(6), 361–373. https://doi-org.ezproxy.snhu.edu/10.1177/0741932514567365

Kurz, A. (2018). Confronting the known unknown: How the concept of opportunity to learn can advance tier 1 instruction. In Elliott, S. N. et al. (eds.), Handbook of accessible instruction and testing practices, Springer International Publishing. http://doi.org/10.1007/978-3-319-71126-3_9

Lebron, R. (2011). *The exploration of the use of data to modify instructional practices by representative teachers in the state of Illinois* (Order No. 3455036). ProQuest Dissertations & Theses Global. (865835013). https://ezproxy.snhu.edu/login?qurl=https%3A%2F%2Fwww.proquest.com%2Fdissertations-theses%2Fexploration-use-data-modify-instructional%2Fdocview%2F865835013%2Fse-2%3Faccountid%3D3783

Leone, E. (2021, October 14). *DOKit! form*. DOK Data Report. http://dokeddatareport.com/#/

Light, D., Wexler, D., & Henize, J. (2004, April). *How practitioners interpret and link data to instruction: Research findings on New York City Schools' implementation of the Grow Network.* Paper presented at the annual meeting of the American Educational Research Association annual meeting, San Diego, CA.

Mahalis, M. (2021). *Education inside a pandemic* (Order No. 28544876). ProQuest Dissertations & Theses Global. (2561437558). https://ezproxy.snhu.edu/login?qurl=https%3A%2F%2Fwww.proquest.com%2Fdissertations-theses%2Feducation-inside-pandemic%2Fdocview%2F2561437558%2Fse-2%3Faccountid%3D3783

Mandinach, E. B., Honey, M., & Light, D. (2006). A theoretical framework for data-driven decision making. In annual meeting of the American Educational Research Association, San Francisco, CA.

Mandinach, E. B., Parton, B. M., Gummer, E. S., & Anderson, R. (2015). Ethical and appropriate data use requires data literacy. *Phi Delta Kappan*, *96*(5), 25–28.

Mandinach, E. B., & Schildkamp, K. (2021a). Misconceptions about data-based decision making in education: An exploration of the literature. *Studies in educational evaluation*, *69*, [100842]. https://doi.org/10.1016/j.stueduc.2020.100842

Mandinach, E. B., & Schildkamp, K. (2021b). The complexity of data-based decision making: An introduction to the special issue. *Studies in educational evaluation*, *69*, [100906]. https://doi.org/10.1016/j.stueduc.2020.100906

McArthur-Blair, J., & Cockell, J. (2018). *Building resilience with appreciative inquiry: A leadership journey through hope, despair, and forgiveness: First edition*. Berrett-Koehler Publishers.

McLaughlin, D. V. (2020). *Personalized principal leadership practices : Eight strategies for leading equitable, high achieving schools*. Emerald Publishing Limited.

Minnesota Department of Education. (2016). *Five categories of educational data: How to use in continuous improvement.* Minnesota Department of Education. https://education.mn.gov/mdeprod/idcplg?IdcService=GET_FILE&dDocName=mde059473&RevisionSelectionMethod=latestReleased&Rendition=primary

Mitchell, C. (2021). *The nation's English-learner population has surged: 3 things to know*. Education Week. https://www.edweek.org/leadership/the-nations-english-learner-population-has-surged-3-things-to-know/2020/02

Mngomezulu, H., Ramaila, S., & Dhurumraj, T. (2022). Pedagogical strategies used to enact formative assessment in science classroom. *International Journal of Higher Education, 11*(3), 158–167.

Morgan, G. (2006). *Images of organization.* SAGE Publications.

My Texas Public School. (2022). *School leadership*. https://www.mytexaspublicschool.org/the-school-system/school-leadership.aspx

Namvar, M., & Intezari, A. (2021). Wise data-driven decision-making. *In D. Dennehy (Eds.), responsible AI and analytics for an ethical and inclusive digitized society: 20th IFIP WG 6.11 conference on e-business, e-services, and e-society, i3e 2021, Galway, Ireland, September 1-3, 2021: Proceedings* (pp. 109–119). essay, Springer. DOI:10.1007/978-3-030-85447-8_10

National Center for Education Statistics (NCES). (2020). *Characteristics of public and private elementary and secondary school teachers in the United States.* U.S. Department of Education, Institute of Education Sciences. https://nces.ed.gov/pubs2020/2020142rev.pdf

National Center for Education Statistics (NCES). (2022). English Learners in Public Schools. *Condition of Education*. U.S. Department of Education, Institute of Education Sciences. https://nces.ed.gov/programs/coe/indicator/cgf.

National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research. (1979). *The Belmont report: Ethical principles and guidelines for the protection of human subjects of research*. U.S. Department of Health and Human Services. https://www.hhs.gov/ohrp/regulations-and-policy/belmont-report/read-the-belmont-report/index.html

National Education Association (NEA). (2020). *Final Appropriations, FY 2021.* National Education Association. https://www.nea.org/sites/default/files/2021-01/FY21%20Final%20Appropriations%20for%20Education%20Related%20Discretionary%20Programs%20with%20State%20Tables.pdf

Nelson, A. J. (2003). *The effect of ESL instruction on student achievement* (Order No. 1413944). Available from ProQuest Dissertations & Theses Global. (305240293). https://ezproxy.snhu.edu/login?qurl=https%3A%2F%2Fwww.proquest.com%2Fdissertations-theses%2Feffect-esl-instruction-on-student-achievement%2Fdocview%2F305240293%2Fse-2%3Faccountid%3D3783

New Hampshire Department of Education. (n.d.). *Minimum standards for privacy and security of student and employee data.* New Hampshire Department of Education. https://www.education.nh.gov/sites/g/files/ehbemt326/files/inline-documents/minimum-standards-privacy.pdf

New Hampshire Department of Education. (2022). *LEP eligible and monitor counts in public school districts.* New Hampshire Department of Education. https://www.education.nh.gov/sites/g/files/ehbemt326/files/inline-documents/sonh/lepenroll21-22v3.pdf

New Hampshire Department of Education. (2021). *2021-22 preliminary allocations report for Title III, part A-ELL.* New Hampshire Department of Education. https://www.education.nh.gov/sites/g/files/ehbemt326/files/inline-documents/sonh/titleiii-parta-prelim-allocations2022.pdf

New Hampshire Department of Education. (2020). *Title III part A sub-grants to LEAs.* New Hampshire Department of Education.

https://www.education.nh.gov/sites/g/files/ehbemt326/files/inline-documents/sonh/titleiii-prelim-2020-21v102220.pdf

New Hampshire Department of Education. (2019a). *Grant sub-award notification.* New Hampshire Department of Education. https://www.education.nh.gov/sites/g/files/ehbemt326/files/files/inline-documents/title-3-final-gan-2019-20.pdf

New Hampshire Department of Education. (2019b). *CFDA 84.365 English language acquisition state grants.* New Hampshire Department of Education. https://www.education.nh.gov/sites/g/files/ehbemt326/files/inline-documents/title3compliance-supplement.pdf

New York State Education Department. (2022). *NYSESLAT general information.* New York State Education Department. http://www.nysed.gov/state-assessment/nyseslat-general-information

Newton, Isaac. (February 5, 1675). [Letter from *Isaac Newton letter to Robert Hooke, 1675*]. https://discover.hsp.org/Record/dc-9792/Description#tabnav

Office of English Language Acquisition (OELA). (2020a, August). *English learners identified and served in state administered Title III programs.* https://ncela.ed.gov/files/fast_facts/20200826-ELsIdentifiedandServed-508.pdf

Office of English Language Acquisition (OELA). (2020b, September). *English learners who speak Spanish as a home language.* https://ncela.ed.gov/files/fast_facts/20200915-Del4-4%20SpanishELs-508.pdf

Oklahoma State Department of Education. (2007). *Caseload/class size requirements*. Oklahoma State Department of Education. https://sde.ok.gov/sites/ok.gov.sde/files/SpecEd-CaseloadClassSize.pdf

Owens, S. (2020). English language learners deserve more: An analysis of Georgia's education for speakers of other languages. *Georgia Budget and Policy Institute.* https://gbpi.org/wp-content/uploads/2020/11/English-Learners-Deserve-More-An-Analysis-of-Georgias-Education-for-Speakers-of-Other-Languages.pdf

Parr, C.S., Jones, T., & Songer, N.B. (2004). Evaluation of a handheld data collection interface for science learning. *Journal of Science Education and Technology* 13, 233–242. https://doi.org/10.1023/B:JOST.0000031262.22712.e0

Poelmans, S., Wessa, P., Milis, K., & van Stee, E. (2009). Modeling educational technology acceptance and satisfaction. *Proceedings of EDULEARN09 conference, 6–8 July 2009, Barcelona* (pp. 5882–5889).

Portz, J., & Beauchamp, N. (2022). Educational accountability and state ESSA plans. *Educational Policy*, *36*(3), 717–747. https://doi-org.ezproxy.snhu.edu/10.1177/0895904820917364

Robinson, M. T. (2021). *The virtual teaching experience with Google Classroom during COVID-19: A phenomenological study* (Order No. 28320244). ProQuest Dissertations & Theses Global. (2563720758). https://ezproxy.snhu.edu/login?qurl=https%3A%2F%2Fwww.proquest.com%2Fdissertations-theses%2Fvirtual-teaching-experience-with-google-classroom%2Fdocview%2F2563720758%2Fse-2%3Faccountid%3D3783

Rowan, B., Camburn, E., & Correnti, R. (2004). Using teacher logs to measure the enacted curriculum: A study of literacy teaching in third-grade classrooms. *Elementary School Journal, 105*(1), 75–101.

Ruf, H. D. (2012). *A comparative study on electronic versus traditional data collection in a special education setting* (Order No. 3525825). ProQuest Dissertations & Theses Global. (1039285067). https://ezproxy.snhu.edu/login?qurl=https%3A%2F%2Fwww.proquest.com%2Fdissertations-theses%2Fcomparative-study-on-electronic-versus%2Fdocview%2F1039285067%2Fse-2%3Faccountid%3D3783

Salkind, N. J. & Frey, B. B. (2020). *Statistics for people who (think they) hate statistics*. SAGE Publications.

Saldaña, J. (2021). *The coding manual for qualitative researchers*. Sage.

Schaaf, R. C. (2015). Creating evidence for practice using data-driven decision making. *American Journal of Occupational Therapy, 69*, 6902360010p6902360011-6902360016.

Schwanke, J. (2020). *The principal reboot: 8 ways to revitalize your school leadership*. ASCD.

Schwartz, H. L., & Diliberti, M. K. (2022). State of the superintendent. Selected Findings from the Fifth American School District Panel Survey. Data Note: Insights from the American Educator Panels. Research Report. RR-A956-12. *RAND Corporation*.

Shaked, D. (2010). A strength-based approach to metrics, scorecards, and performance reviews. *AI Practitioner, 12:3, 50-55*

Singh, L. (2011). Accuracy of web survey data: The state of research on factual questions in surveys. *Information Management and Business Review*, *3*(2), pp. 48-56. https://doi.org/10.22610/imbr.v3i2.916

Sivic Solutions Group. (2022, April 20). *Education.* http://sivicsolutionsgroup.com/education.html

Skinner, R. R. (2019). *The elementary and secondary education act (ESEA), as amended by the every student succeeds act (ESSA): A primer (Report No. R45977)*. Congressional Research Services. https://crsreports.congress.gov/

Stecker, P. M., Fuch, L. S., & Fuchs, D. (2005). Using curriculum-based measurement to improve student achievement: Review of research. Psychology in Schools, 42(8), 795-819. http://doi.org/10.1002/pits.20113

Tamim, S., & Torres, K. M. (2022). Evolution of the dissertation in practice. *Impacting Education: Journal on Transforming Professional Practice*, *7*(1), 1–3. https://doi.org/10.5195/ie.2022.267

Tarbox, J., Wilke, A., Findel-Pyles, R. S., Bergstrom, R. M., & Granpeesheh, D. (2010). A comparison of electronic to traditional pen-and-paper data collection in discrete trial training for children with autism. *Research in Autism Spectrum Disorders, 4*(1), 65-75.

TESOL. (2023a). *Principle 1: Know your learners.* TESOL. https://www.the6principles.org/the-principles/principle-1/

TESOL. (2023b). *Principle 5: Monitor and assess student language development.* TESOL. https://www.the6principles.org/the-principles/principle-5/

TESOL. (2023c). *The 6 principles for exemplary teaching of English learners.* TESOL. https://www.the6principles.org/the-principles/

TESOL Quarterly. Wiley Online Library. (2023). https://onlinelibrary.wiley.com/journal/15457249

The Campaign for Educational Equity. (2014). *Know your rights: English language learner resource requirements*. Columbia University. http://www.centerforeducationalequity.org/publications/know-your-educational-rights/31868_ELL_KYR_6.10.pdf

Thompson, B., Diamond, K., McWilliam, R., Snyder, P., & Snyder, S. (2005). Evaluating the quality indicators from correlational research for evidence-based practice. *Exceptional Children. 71*(2), 181-193.

Todman, J. B., & Dugard, P. (2001). *Single-case and small-n experimental designs: A practical guide to randomization tests.* Lawrence Erlbaum Associates Publishers.

UnidosUS. (2018a, May). How are states including English language proficiency in ESSA plans. https://unidosus.org/publications/1872-how-are-states-including-english-language-proficiency-in-essa-plans/

UnidosUS. (2018b, May). *How have states set goals for English learners in ESSA plans.* https://unidosus.org/publications/1871-how-have-states-set-goals-for-english-learners-in-essa-plans/

United States Department of Education. (2022a). *FY2023 president's budget.* United States Department of Education. https://www2.ed.gov/about/overview/budget/budget23/summary/23summary.pdf

United States Department of Education. (2022b). *Operating structure.* United States Department of Education. https://www2.ed.gov/about/offices/or/index.html

United States Department of Education. (2021). *Dr. Miguel Cardona, secretary of education-biography.* United States Department of Education. https://www2.ed.gov/news/staff/bios/cardona.html

United States Department of Education. (2018). *An overview of U.S. department of education.* United States Department of Education. https://www2.ed.gov/about/overview/focus/what.html

Usher, M., Hershkovitz, A., & Forkosh-Baruch, A. (2021). From data to actions: Instructors' decision-making based on learners' data in online emergency remote teaching. *British Journal of Educational Technology*, *52*(4), 1338. https://doi-org.ezproxy.snhu.edu/10.1111/bjet.13108

Vail, K. (2022). What's beyond the pandemic accountability freeze? *Phi Delta Kappan*, *104*(3), 30–35. https://doi-org.ezproxy.snhu.edu/10.1177/00317217221136596

Villegas, L. & Pompa, D. (2020). *The Patchy Landscape of State English Learner Policies under ESSA.* The Migration Policy Institute. https://www.migrationpolicy.org/sites/default/files/publications/ESSA-Compendium-Final.pdf

Visscher, A. J. (2021). On the value of data-based decision making in education: The evidence from six intervention studies. *Studies in Educational Evaluation*, *69*. https://doi-org.ezproxy.snhu.edu/10.1016/j.stueduc.2020.100899

Waters, T. J. & Marzano, R. J. (2006). School district leadership that works: The effect of superintendent leadership on student achievement. A Working Paper. Mid-Continent Research for Education and Learning (McREL).

WIDA. (2022). *Proven tools and support to help educators and multilingual learners succeed*. WIDA. https://wida.wisc.edu/

WIDA. (2023). *ACCESS for ELLs Interpretive Guide for Score Reports.* WIDA. https://wida.wisc.edu/sites/default/files/resource/Interpretive-Guide.pdf

Williams, C. (2020). The case for expanding federal funding for English learners. *The Century Foundation.* https://tcf.org/content/commentary/case-expanding-federal-funding-english-learners/

Wiseman, A. W. & Bell, J. C. (2021). Education without evidence: Gaps in data availability for refugee, asylee, and humanitarian migrant students in US schools. *Research in Education*, 1. https://doi-org.ezproxy.snhu.edu/10.1177/00345237211034885

Wright, J. (2006). *Principals' use of data for school improvement decisions.* Unpublished Dissertation, Aurora University, Aurora, IL.

Wu, M.-J., Zhao, K., & Fils-Aime, F. (2022). Response rates of online surveys in published research: A meta-analysis. *Computers in Human Behavior Reports*, *7*. https://doi-org.ezproxy.snhu.edu/10.1016/j.chbr.2022.100206

Yen, E. L. Y., & Mohamad, M. (2021). Spelling mastery via Google Classroom among year 4 elementary school ESL students during the COVID-19 pandemic. *Journal of Education and E-Learning Research*, *8*(2), 206–215.

Young, C., McNamara, G., Brown, M., & O'Hara, J. (2018). Adopting and adapting: School leaders in the age of data-informed decision making. *Educational Assessment, Evaluation and Accountability*, *30*(2), 133–158.

Zigmund, L. D. C. (2021). *Investigating teachers' use of data-driven decision-making in Northeastern Pennsylvania public schools* (Order No. 28323853). ProQuest Dissertations & Theses Global. (2509238742). https://ezproxy.snhu.edu/login?qurl=https%3A%2F%2Fwww.proquest.com%2Fdissertations-theses%2Finvestigating-teachers-use-data-driven-decision%2Fdocview%2F2509238742%2Fse-2%3Faccountid%3D3783

Appendices

Appendix A

***A Survey to Assess Data Use in Educational Decision-Making* (modified for ELD)**

Exploring Data-driven Decision Making in English Language Development, Title III

This survey quantitatively explores the strength of the association between

teachers' experience teaching English language development

and

data-driven decision-making.

Survey data will be collected from Title III participants using a voluntary response sample considering Thomson et al.'s (2005) Quality Indicators for correlational research. Following the research design elements utilized by Lebron (2011) and Zigmund (2020), careful considerations were made regarding implementing the correlational study using the survey tool in public school settings. The survey will collect data on teachers' years of experience and the utilization of different types of data, data analysis, and data reports. This survey is entirely anonymous.

Required

Survey Consent

Do you consent to the anonymous research using this survey you are about to complete? *

Mark only one oval.

◯ Yes

◯ No

Demographic

1. Select the option that best describes your gender *

Mark only one oval.

- Female
- Male
- Prefer not to say

2. Select the option that best describes your race *

Mark only one oval.

- Asian/Pacific Islander
- Black
- Caucasian (Non-Hispanic)
- Hispanic
- Multi-Racial/Ethnic
- Native American

3. Select the option that best describes the grade level of the ELLs you teach *

Check all that apply.

- [ ] K-2
- [ ] 3-6
- [ ] 7-9
- [ ] 10-12

4. What is the number of years that you have been employed as a public school teacher for ELLs? (if between 1 month - 11 months, respond 1) (numerical value only)

5. Does your district participate in any of the following federal programs (check all that apply)

Check all that apply.

- [ ] ESSA Title III
- [ ] unsure

6. What is your age (enter a numerical value) *

Data Collection

Respond if you use the following type(s) of data for English language development educational decisions related to change in your instructional practices.

Then, rate the importance of each type of data to change your instructional practice for additive instructional scenarios for English language development.

7a. Standardized Tests, including State Assessments *

Mark only one oval.

- ( ) Yes
- ( ) No

›. Rank the importance of the previous type of data when making nstructional decisions *

Ⅵark only one oval.

	1	2	3	4	5	
Completely Unimportant	⬭	⬭	⬭	⬭	⬭	Extremely important

8a. WIDA ACCESS scores *

Mark only one oval.

⬭ Yes

⬭ No

b. Rank the importance of the previous type of data when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant	⬭	⬭	⬭	⬭	⬭	Extremely important

9a. Student performance measures developed by your district

Mark only one oval.

⬭ Yes

⬭ No

b. Rank the importance of the previous type of data when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant	◯	◯	◯	◯	◯	Extremely important

10a. Classroom assessments developed by teachers (including yourself) *

Mark only one oval.

◯ Yes

◯ No

b. Rank the importance of the previous type of data when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant	◯	◯	◯	◯	◯	Extremely important

11a. Student portfolios *

Mark only one oval.

◯ Yes

◯ No

b. Rank the importance of the previous type of data when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant	○	○	○	○	○	Extremely important

12a. Retention rates *

Mark only one oval.

○ Yes

○ No

b. Rank the importance of the previous type of data when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant	○	○	○	○	○	Extremely important

13a. Graduation rates

Mark only one oval.

○ Yes

○ No

b. Rank the importance of the previous type of data when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant	⬭	⬭	⬭	⬭	⬭	Extremely important

14a. Attendance in English Language Development groups or in-class English support *

Mark only one oval.

- ⬭ Yes
- ⬭ No

b. Rank the importance of the previous type of data when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant	⬭	⬭	⬭	⬭	⬭	Extremely important

15a. Student discipline and behaviors *

Mark only one oval.

- ⬭ Yes
- ⬭ No

b. Rank the importance of the previous type of data when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant	◯	◯	◯	◯	◯	Extremely important

16a. Perceptions of parents *

Mark only one oval.

◯ Yes

◯ No

b. Rank the importance of the previous type of data when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant	◯	◯	◯	◯	◯	Extremely important

17a. Perceptions of teachers in your school (include yourself) *

Mark only one oval.

◯ Yes

◯ No

b. Rank the importance of the previous type of data when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant	◯	◯	◯	◯	◯	Extremely important

18a. Perceptions of students *

Mark only one oval.

◯ Yes

◯ No

b. Rank the importance of the previous type of data when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant	◯	◯	◯	◯	◯	Extremely important

19a. Instructional servicing strategies (i.e. pull out, push in, co-teaching, remote, or lesson details) *

Mark only one oval.

◯ Yes

◯ No

b. Rank the importance of the previous type of data when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant	◯	◯	◯	◯	◯	Extremely important

20a. Instructional servicing time (i.e. how long were students instructed by an ELD teacher in the additive instructional setting?) *

Mark only one oval.

◯ Yes

◯ No

b. Rank the importance of the previous type of data when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant	◯	◯	◯	◯	◯	Extremely important

Data Analysis

Do you use the following type of data analysis for decisions related to changing your instructional practices? For the purpose of this study, data analysis is defined as methods of studying data to determine its essential features and their relationship with other data.

21a. Identification of trends and patterns over time *

Mark only one oval.

- Yes
- No

b. Rank the importance of the previous type of data analysis when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant						Extremely important

22a. Identification of trends and patterns at one point in time *

Mark only one oval.

- Yes
- No

b. Rank the importance of the previous type of data analysis when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant						Extremely important

23a. Chart progress of subgroups of students *

Mark only one oval.

- Yes
- No

b. Rank the importance of the previous type of data analysis when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant						Extremely important

24a. Chart the progress of individual students *

Mark only one oval.

- Yes
- No

b. Rank the importance of the previous type of data when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant						Extremely important

25a. Intersect two types of data (i.e. how gender affects performance in English language development?) *

Mark only one oval.

- Yes
- No

b. Rank the importance of the previous type of data analysis when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant						Extremely important

26a. Intersect three types of data (i.e. how gender and attitude affect performance in English language development?) *

Mark only one oval.

- Yes
- No

b. Rank the importance of the previous type of data analysis when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant						Extremely important

27a. Intersect four types of data (i.e. how gender, attitude, and instructional strategies affect performance in English language development?) *

Mark only one oval.

- Yes
- No

b. Rank the importance of the previous type of data analysis when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant						Extremely important

28a. Pose questions and hypotheses and then analyze data to find answers *

Mark only one oval.

- Yes
- No

b. Rank the importance of the previous type of data analysis when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant						Extremely important

29a. Create reports based on the data analysis to present your findings *

Mark only one oval.

- Yes
- No

b. Rank the importance of the previous type of data analysis when making instructional decisions *

Mark only one oval.

	1	2	3	4	5	
Completely Unimportant						Extremely important

Conclusion: Open Ended

30. In as much detail as possible, explain how you collect, use, and report data when making instructional decisions for ELLs in your school *

31a. Have you ever participated in any of the following

Check all that apply.

- [ ] Professional Development of Data Collection
- [ ] Professional Development of Data Analyzation
- [ ] Data-Driven Community Practice
- [ ] College Course on Data Collection and Analyzation
- [ ] A Workshop or Seminar on Data Collection and Analyzation

31b. In as much detail as possible, explain the details of the professional learning you have experienced with data collection and analyzation

Appendix B

Permission from Zigmund to Modify Questionnaire

Elizabeth Leone <lizlynn1218@gmail.com> Mon, Oct 10, 2022 at 1:44 PM
To: "lzigmund@wbasd.k12.pa.us" <lzigmund@wbasd.k12.pa.us>

Good afternoon,

My name is Elizabeth and I am working on my doctorate in educational leadership with a dissertation focused on the lack of educational data on refugee and immigrant students. I designed an innovation for documenting and reporting English language development data, but first I would like to complete my research on current educational data practices in public school settings in New Hampshire English language development programs.

I am very excited about your work as your survey fits very closely with my intended purpose of exploring data practices. Do you allow students to use this tool for dissertation purposes? My study is a correlational study with similar questions but focused on Title III programs. Would you allow some slight modifications to the wording to fit the topic better (for example, "Title III educators" instead of "teachers")?
I would also love to talk more about some of your research if your schedule allows.

Thank you so much for your time and in advance for your response!

Best,
Elizabeth Leone
--
Elizabeth Leone
ESOL teacher
Jewett Street Elementary School
Manchester NH
717-614-0685
eleone@mansd.org

Zigmund, Leah <lzigmund@wbasd.k12.pa.us> Thu, Oct 13, 2022 at 11:51 AM
To: Elizabeth Leone <lizlynn1218@gmail.com>

Hello Elizabeth,

Let me first apologize for the delay in my response as I remember how much it meant to me when I was completing my own research.

Yes, you may use and modify the survey tool utilized in my research. Please let me know if I can do anything else to support you.

Best wishes in your educational pursuit!

Leah
[Quoted text hidden]
--
Dr. Leah Zigmund
Federal Programs Coordinator
Wilkes-Barre Area School District
570.826.7111 x 1145

Appendix C

Sample Consent Letter to School Districts

Sample School District
Contact Person
School District Address

12/15/2022

Dear Superintendent [name]

<u>Re: Permission to conduct research at [School District Name]</u>.

My name is Elizabeth Leone. I am a doctoral candidate studying for my EdD at Southern New Hampshire University with a dissertation focused on policies pertaining to the subgroup of English language learners. I am seeking permission to do research in your district regarding your English language development program.

I am researching data collection and analysis in ESSA Title III: English language development programs. The research will entail collecting anonymous data from English as a second language teachers in multiple districts through a short 10-15 minute survey. The survey quantitatively explores the strength of the association between teachers' length of experience teaching English language development and data-driven decision-making, utilization of different types of data, data analysis, and data reports.

With your permission, I will invite individuals from your organization's English language development program to participate in this study in mid-January. Survey data will be collected from Title III participants using a voluntary response sample considering Thomson et al.'s (2005) Quality Indicators for correlational research. Careful considerations were made regarding implementing the correlational study using the survey tool in public school settings. The survey was designed and vetted for validity and reliability by Cronin (2001). For access to the survey, please follow the link: https://forms.gle/sHmcEcVLGZBxrJMr8

Participants will be asked to give their consent before the research begins. Their responses will be treated confidentially, and the identities of teachers and districts will be completely anonymous. The study results will be communicated in a dissertation, and I will submit to you any anonymous results obtained from teachers at any time.

The research participants and districts will not be advantaged or disadvantaged in any way. Participants will be reassured that they can withdraw at any time during this project without any penalty. There are no foreseeable risks in participating in this study for teachers or districts, especially as the focus is on ESSA Title III and not the individual districts. The participants will not be paid for this study. All research data will be preserved anonymously for reuse in future research or destroyed after analysis.

I, therefore, request permission in writing to conduct my research at your organization. The permission letter should be on your organization's headed paper, signed and dated, and specifically referring to me by name and the title of my study.

Please let me know if you require any further information. I look forward to your response as soon as it is convenient.

Sincerely,

Elizabeth Leone, M.Ed.
Researcher
elizabeth.leone1@snhu.edu

Irving Richardson, EdD
Doctoral Committee Chair
i.richardson@snhu.edu

Appendix D

Sample Endorsement Letter for School District Use

Dear Teachers

I am writing to inform you that Ms. Leone will be contacting you regarding a survey for English as a second language teachers. She is a doctoral candidate studying at Southern New Hampshire University with a dissertation focused on policies pertaining to the subgroup of English language learners and ESSA Title III. Our district has endorsed her research survey in our district's English language development program. Ms. Leone describes her research in the following;

> "I am conducting research on data collection and analyzation in ESSA Title III: English language development programs. The research will entail collecting data from English as a second language teachers in multiple districts through a short 10-15 minute survey. The survey quantitatively explores the strength of the association between teachers' length of experience teaching English language development and data-driven decision-making, utilization of different types of data, data analysis, and data reports."

The survey is completely voluntary and anonymous. Participants will be asked to give their consent before the survey begins. The research participants and districts will not be advantaged or disadvantaged in any way. Participants can withdraw at any time during this project without any penalty. There are no foreseeable risks in participating in this study for teachers or districts, especially as the focus is on ESSA Title III and not the individual districts. The participants will not be paid for this study.

Our district has permitted this survey to be administered to our English as a second language teacher. We encourage you to provide your feedback as research is a valued part of the educational system. Please follow the link: https://forms.gle/sHmcEcVLGZBxrJMr8

Thank you for all that you do every day!

Sincerely,

[name]

Appendix E

Title III Program Assurances

According to the Bureau of Federal Compliance (Carney, 2020), the fiscal year program assurances for all Title III, ESSA programs are the following;

1. Consult with others on plan development
2. Assess English proficiency yearly
3. Use effective approaches and strategies
4. Comply with private school participation requirements
5. Assess ELLs in English
6. Be in compliance with state laws
7. Use Title III funds to supplement, not supplant other resources
8. Use of funds for ESL
9. Select methods for effective instruction
10. Comply with parent requests for information about staff educating their children
11. Coordinate with Head Start
12. Use of immigrant set-aside funds (Carney, 2020)

Appendix F

ELD Teacher Open-ended Responses for Data Collection and Analyzation

Response Number	Response
1	First I discuss the data from the WIDA ACCESS tests with the other ESL teachers in the district. We go over our students and the test results. We collectively may decide the best approach for the following school year. For example: If a student tested well in 3 domains but was low in writing, we will probably recommend the main focus to be writing. The pull out times/minutes will be in accordance to the low score a student with a score below 3.5 probably will be pulled out 5 days a week. A student with a score above that 2/3 times a week. We also consider the student culture and temperament. At Underhill we look at the NWEA and DIBELS data when making instructional decisions.
2	ELL Student work, IReady scores, Access scores, Core classroom classwork, specialized services feedback. Collaborating with other teachers and reviewing test data helps to inform instruction.
3	We don't gather ELL specific data other than the Screener and ACCESS. The district uses mainstream assessments to compare mainstream vs ELL performance.
4	School & district collect data from student performance on both summative and formative tasks, standardized tests, I-Ready data, and progress over time in an attempt to make instructional & placement decisions, however, we are hampered by lack of staff & resources.
5	We look at data from classroom teachers summative and formative assessments, state test scores, access test scores, regular F and P reading scores, aimsweb results and data that emerges from Le1ia usage on a regular basis during collaborative meetings with EL, spec.ed, classroom teacher and administrative staff. This is a piece of the picture, that includes classroom work and daily observation/formative assessments. Looking at this data we determine if our current curricular strategies are yielding growth, and if that growth is moving in an accelerated way to close the gap with grade level curriculum.
6	The more data collected for ELLs the best. I get to k0w my students and I use this data to help Ells according to their needs.
7	I create portfolios for each students with their work to see progress over time and what they need to still work on or whether they need to move on. We use WIDA testing and collect data though testing scores.
8	I collect data on my own using online systems and outcomes that are in a student's cum file such as ACCESS, NWEA and reading Benchmarks. I use this data to schedule service minutes and plan lessons. I report data to classroom teachers and

	parents and together we discuss how to best meet the EL's needs.
9	Our schools collect and graph student progress in Math, ELA, and SEL, we also look closely at ACCESS data to identify gaps and target instruction. This data is used to identify students in need and to create instructional groupings. ACCESS proficiency data is also used to advocate for service minutes for ELs, but unfortunately these are just recommendations in New Hampshire and our administrators do 0t see the need to meet recommendations for ESOL support minutes.
10	We use the WIDA screener to screen any potential ELLs. We follow a curriculum for our ELLs and support classroom content by following and supporting mainstream teacher curriculum as well. We document and keep everything. We administer the ACCESS for ELLs test in February and March.
11	I am also not a data driven teacher. This is influenced by the fact that I work at a very low ESOL populated school, so I tend to plan for students on an individual level. I trouble shoot extensively with the classroom and other support teachers. My experience has also been that my ESOL students, generally, are high achievers with very supportive families. The data that informs me the most is the ACCESS Test scores, their report cards and collaborative planning from and with classroom teachers.
12	We collect data from Iready, Access, Imagine Learning, and create a tailored instructional plan for each student in terms of language and linguistic goals for our students. We progress monitor along the way to see if our students are making progress towards those goals.
13	Portfolios, 0tebooks, performance ratings, and conferences with students
14	data collection is not a focus of my instructional practices
15	I collect data through ACCESS scores and student course grades, as well as through work in my classroom. I do direct my teaching based on test scores to some extent, but by in large I use informal data collected through interactions with students to direct my lessons and instructional time.
16	Google doc forms
17	data collection is not a huge part of my daily practice as an ELL teacher.
18	I keep a daily attendance record, as well as, alphabet and sight word lists with most students with wida 2 or higher proficiency. I use my data to show change over time, development of language. I do 0t report my data.
19	I only look at yearly ACCESS scores to plan with teachers and use this as support data in IEP meetings or family meetings.
20	follow lessons on district curriculum, do not take attendance or collect any data, I use wida access scores

21	I use a combination of iReady scores and Access scores. These are the most helpful to me. I probably rely on iReady scores more as Access scores as the tests are taken in Feb. and by Sept the students usually have made more growth.
22	The only formal data collection we use for ELs is ACCESS test scores and we are only just starting to look at EL- specific iReady scores
23	Really, I do what is asked of me in terms of ACCESS and iReady. More informally, I look at individual students and their progress and growth over time, on those assessments and in their class work. I am cautious make many generalizations about what data says about ELs in general since they are such a diverse group of students.
24	We use ACCESS, Iready, DIBELS scores as well as classroom performance data from classroom teachers to make instructional decisions.
25	Daily observation notes, spreadsheets of data for each student based on ACCESS, Iready scores, Dibbels, and goal setting for students
26	I use the system Ellevation to collect and analyze data from WIDA scores. I make my own data charts to collect and measure data from class organized in google drive. I use google sheets to track the assessments that I perform.
27	surveys, data management platforms, student information system, create my own spreadsheet, interviews, iplatform
28	Using i4See rosters, Aspen data, ACCESS scores, and reviewing individual student data for placement, support, services, and language and academic progress.
29	WIDA scores and individual writing journals, content classroom grades.
30	Data is tracked on a number of levels, including state, local, and EL-specific assessments. This data is used to determine service levels, assign interventions, and target specific skills.
31	I take my students and observe their progress, data is 0t required and it takes too much time.
32	I discuss with classroom teachers student scores on district and state assessments. WIDA scores direct instructional groups.
33	attendance sheet, informal assessments, oral checks, sight word
34	I mostly use unit quizzes and unit assessments to drive my instruction, since these are happening in real time. As well as direct input from the classroom teachers. If a student is struggling in a particular area in the classroom I will add that practice into my lesson for that student. When I take unit assessments I record these into a spreadsheet for each student, I then note if a particular student or whole group struggled with a particular area; i.e.. Grammar, or vocabulary. Then I build in e1tra practice, into my ne1t few lessons, around this topic. I use the WIDA access testing to determine where the student is struggling over all. This helps me build beginning lessons for the start of the school year as well as when I receive new students throughout the year.

35	As a elementary school teacher we have the unique ability to speak with all teachers effecting our El students learning. Because of this we can hypothesize our ideas of what barriers they may be facing and group accordingly and test to see if our ideas were correct. The fle1ibility we have in Elementary school allows for better meeting the needs of our EL students.
36	We use a variety of assessments, formal and informal to make instructional decisions -- WIDA screener or ACCESS, district reading benchmarks, Vista curriculum unit tests *NEW THIS YEAR* to determine student instructional groupings for EL pullout groups and classroom placement for the upcoming year (at our school we coteach with classroom teachers and make student groupings on the number of minutes required/duel coded EL students who we have to share with SPED)
37	I have, in the past, been involved in grade level PLCs but are not any longer in this building. I find this frustrating because with our limited amount of instructional time, I appreciate observational and other data collected by classroom teachers to take into consideration. I also find frustrating that our instructional services are dictated by ACCESS score only- a set of data that is 6+ months old by the time we use it. I personally and as a district we are working toward finding quick and easy to collect data to track student progress and achievement. Often this data is not shared with classroom teachers unless something is alarming.
38	Collaboration with teacher, observations, classroom quizzes, end of unit assessments.
39	I collect data such as quizzes, tests, classwork periodically. I also collect less formal data on how my students do on basic classroom tasks. Depending on the type of data, I may keep originals, or just the numerical data of student scores. For writing, I collect samples and score with rubrics. I use data for many reasons. One reason is to check my own instruction. If many or most of the students in a group are struggling with a concept, I know that I need to revisit it, teach it again in a new way, give students more practice, and check in on what may be confusing for them. As an EL team, we also use data to put students into groups that make the most sense. 0t all of the students can be in the same group, but we can use data to make groups that will be most effective. Reporting is 0t a strength of mine. I often go back and forth in finding the best way to organize the data to be user-friendly, but also contain the crucial data. I do use many tables, charts, and spreadsheets in order to report out my data. However, many
40	I use and collect data for the English Learner Plan (ELP) that includes info from as many sources as possible to provide a clearer reflection on what an EL is at different moments in time as well as how their past performance may predict future achievement.
41	I use district testing, state testing, summative, and formative assessments and observations from classroom, RTI , ELL, UA teachers to collect data when making instructional decisions
42	Due to time constraints, I must be brief. I use the data collected to make instructional decisions, class(and teacher) placement decisions and to inform students, parents,

	teachers and admin overview of student progress. I also use data to analyze my teaching strategies.
43	I have used data collection during course work and within my professional experience. Data collection is often based on school wide assessments or mandated assessment measures. When students are in a small group settings, goals are created and measured based on their individual needs and measured using provided resources. Instructional decisions are always comple1 decisions that require the analysis of data, along with professional judgement and observations of students' work and progress. Data collection and analysis are important parts of instructional decisions, and I always use data to drive my instruction. But, the individual student's needs and situation, as well as my professional experience are factors that are considered along with data.

Appendix G

ELD Teacher Open-ended Responses for Professional Learning Experiences

Response Number	Responses
1	I have attended various PD with WIDA regarding how to use data to decide instruction based on the results of the WIDA ACCESS tests.
2	I have not had any PD around data collection and analyzation.
3	no
4	Participation in both WIDA seminars & district sponsored PD around data collection and analysis (how do scores correlate to performance & grade level tasks) in the hopes of improving access to curriculum; mi1ed results due to staffing & resource shortages. Our program is severely underfunded & under resourced.
5	This professional learning has taken place on an ongoing basis through staff inservices with data team, to familiarize the teaching staff with the different ways in which we can aggregate and analyze data both for the school at large and for individual students
6	I try to gather as much data possible. This includes: Home assessment- data entry record of parent contact (country, language, culture) Observation progress in speaking using assessment formal and informal. Writing folders- writing samples Standardized test scores Student profile from previews years Reading - Benchmarks for the grade level and indicators of which ones had been reached. This data is used to show growth and to demonstrate mastery of standards. Parents-teacher conference reports WIDA ACCESS is used to determine the language level of proficiency. This test ensures standardized reliable scoring. It is organized by language domains: Speaking, Listening, Reading and Writing.
7	I have not received any instructional learning just my own from doing this in my classroom
8	I just completed WIDA’s Multi-Tiered Systems of Support workshop. The activities, online videos and readings provided information about the importance of collecting and analyzing data to support the educational and mental health of multilingual learners.

9	It has been a long time since I have attended trainings on these topics. I have attended workshops on this topic at the DoE, with WIDA, Renaissance, and I believe with Demonstrated Success. This survey does not feel confidential when we are asked to include email and age Good Luck with your research project!
10	I have experience with Data Collection only in terms of our screener and the ACCESS test.
11	I have participated in one or two seminars that explained the break down of scores from State Testing and it was informative. Offered and dispassionate view.
12	I have not participated in PD related to data collection/ analysis
13	WIDA sponsored workshops and seminars
14	college course on assessment discussed using data
15	I use the ACCESS and report on individual and class achievement of students.
16	Several College level courses during my masters programs
17	0
18	none
19	state ran a seminar a few years ago on assessment data and I complete a yearly recertification for WIDA and SAS testing that takes over 10 hours. This is on administration of assessments but hits on the data collection
20	none, some personal research
21	Our school talks about data at PLCs but as a whole I have not done much with it.
22	My previous school had a data team and we had regular staff workshops on data analysis on iReady scores
23	I have taken part in district PD on data analysis, the cycle. I have taken graduate level statistics in education classes. I am currently in the midst of an action research project which involves collecting and analyzing data.
24	We have use PLC time with our curriculum coaches to learn how to look at Iready test score data and DIBELs data to analyze and drive instruction.
25	I have never attended PD on data
26	not much- just a few webinars here and there.
27	I have participated in multiple action research studies. Some in partnership with a local university. I have also utilized data collection techniques such as soliciting the voice of a target group related to a topic and then coding the data to analyze for follow up actions.
28	not enough to make the decisions needed to successfully support students.

29	I have participated in all of the above at some point during my teaching career and when I was required to complete data collection and analyzation courses while acquiring my CAGS.
30	Professional learning in using ACCESS data and scale scores to determine student progress in accessing classroom instruction.
31	Don’t collect data
32	Data collection and analyses are 0t regularly offered for ELL teachers
33	I sought out assessment strategies and rubric assessments on my own, as well as district training on some phonics and ELD tests (Fontas and Phinnel)
34	While this is my first year as an ELL teacher. I have taught SpEd for 22 years. I have taken courses as well as on going workshops on data collection and analysis. I was part of a data team at one of my schools for 3 years - we met to review SAS test scores for the entire building and determine areas of weakness in order to help classroom teachers improve their instruction in those areas. For instance bringing in a new phonics program, as well as working with the 4th and 5th grade teachers to design and implement more structured Science experiments and reports. I also worked closely with the Reading specialist, every year, to review grade level data and determine the students who needed intervention as well as the type of intervention needed We then designed groups to focus on those needs. Typically we review data collection and it’s importance to use the data to drive instruction on a early basis at a faculty meeting. It is really up to the individual to seek out professional learning in this area on their own.
35	On leadership (a committee in our school) and during collaboration meetings weekly we take the time out to look at Data of different assessments of our students to notice strengths and weaknesses as well as trends to see where we can better meet the needs of our students. We also take the time in our collaboration meetings to discuss the progress of individual students so that we may continue to provide them with the skills needed to fill the gaps in their learning.
36	At my school, we are usually excluded from data analysis PLCs. We participate in CHAT initial meetings but they are not conducted in a typical manner - it’s an alternative format with only the classroom teacher and principal (and EL if we are informed/invited). In the beginning of the year, we attended a training on PLC norms but have been excluded from grade level PLCs
37	Most of this learning recently has been in literacy with my additional degree in reading and writing. In a former placement, we used a strict protocol to analyze data in PLcs.
38	How to collect data and analyze student performance. This is beneficial if the student is struggling. This helps to identify both strengths and weaknesses and in turn, drives instruction and influences pacing and if a student needs re-teaching and is ready for more challenging content.

39	I attended a training put on by Demonstrated Success about analyzing and leveraging SAS data.
40	Have used data to make decisions for classes, for presentations, and otherwise in public schools and in higher education, as student, and as instructor.
41	none
42	I've had at several grad level courses but also rely on my e1perience and my colleagues expertise for input regarding the value of data. For example, a 'single snapshot in time' type of assessment or performance data vs a longitudinal analysis or progress overtime to make informed instructional decisions. I feel sometimes so much time is spent on the testing and data when in reality we must focus on building relationships with students and quality, consistent instruction.
43	n/a

Appendix H

DOKed Professional Learning Experience (PL) outline

During the launch of the intervention, each teacher will receive 2 hours of PL bi-weekly for the first two months and once a month for the next 10 months. The learning will include the importance of data collection and analyzation, how to identify Opportunity to Learn (OTL), and documentation procedures. This PL experience will incorporate DDDM, data equity, and data literacy frames. This training will also prepare participants to administer DOKed in their classrooms and schools, enroll students and co-teacher, and troubleshoot common difficulties. Participants will be prepared to complete the daily DOKit! form, understand the data on the dashboard, and disaggregate the reports for themselves and for collaboration purposes. PL participants will include an opportunity to view and analyze reports with other participants and a facilitator before being expected to create and analyze classroom data reports from the participants' classrooms. The 26-week PL will address the following topics.

1. What is data?
2. Data Efficacy
3. Data for efficacy
4. Data for ELD
5. Data analysis
6. Data reporting
7. Presenting data