LANGUAGE MATTERS: LENA TECHNOLOGY IN RESEARCH AND PRACTICE

By

Sarah M. Avendaño

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ABSTRACT

Early Expressive language exposure is associated with child language acquisition and advantageous long-term developmental outcomes. The measurement of expressive language in a child's immediate environment is critical to the early identification of children who are at risk of low expressive language exposure, such as children with language delays or disabilities including Autism Spectrum Disorder (ASD). A team of researchers, educators, and engineers developed Language ENvironmental Analysis™ (LENA), a computerized language processing software, to ease the language sampling process. Recently, language acquisition researchers have proposed that LENA technology has greater application in clinical practice to collect naturalistic language acquisition data to inform educational services. Therefore, the present dissertation investigated the use of LENA technology in applied research, uses LENA technology to take naturalistic repeated measures in a clinical setting, and makes suggestions for clinical research (see Chapter 2, 3, and 4).

Chapter 2 was a systematic literature review of the use of LENA technology in applied research to identify information on study methodology, LENA technology implementation, and the use of novel variables derived from LENA technology in applied research. The results showed that researchers are increasingly using LENA technology with more diverse populations and using more diverse LENA measures to measure the language environment. Specifically, the number of different languages, ethnicities, and abilities have increased in research using LENA technology to evaluate language environments. However future research needs to include better descriptions of procedural information, which is critical for an emerging body of research.

Chapter 3 depicted the expressive language trajectories of preschool-aged children with ASD who are receiving Early Intensive Behavioral Intervention (EIBI). Overall, the present

investigation demonstrates that minimally verbal pre-school aged children with ASD demonstrate growth in expressive language trajectory in EIBI and that EIBI may be equally beneficial, in terms of expressive language growth, for children of all expressive language levels. The authors observed a waxing and waning of child language growth over the course of a year, consistent with prior research that highlights the importance of measuring individual child expressive language trajectories in research

Finally, Chapter 4 introduced LENA technology as a behavioral observation measure to behavior analytic practitioners to improve the language environment of young children with ASD. Discussions of what LENA programs are available for behavior analytic use with young children with ASD, how practitioners can use LENA technology in behavior analytic services, and considerations for practical use of LENA in behavior analytic services. The authors provided examples throughout the paper to illustrate the use of LENA technology in behavior analytic practice to improve the language environments of young children with ASD.

I dedicate this dissertation to my dad, who is my superhero.

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LIST OF ABBREVIATIONS

AWC: Adult Word Count

TC: Conversational Turns Counts

CV: Child Vocalizations

VR: Vocalization Ratio

DLP: Digital Language Processor

EIBI: Early Intensive Behavioral Intervention

LENA: Language Environment Analysis

PRISMA: Preferred Reporting Items for Systematic reviews and Meta-Analyses

RBT: Registered Behavior Technician

SES: Social Economic Status

CHAPTER 1: INTRODUCTION

Suskind et al. (2015) described caregiver language spoken to young children as one of the most precious resources in the world. Since the 1960 war on poverty in the United States, researchers across disciplines have studied early language exposure and the advantageous effect language exposure has on the development of children with and without disabilities. The children who benefit from higher levels of caregiver language before beginning school garner developmental advantages immediately upon entering school and throughout their lifetime.

Early Language Exposure

The first three years of a child's life is a critical developmental period that affects long term achievement. Research has demonstrated that child language acquisition is particularly sensitive to the quantity of caregiver language exposure during that early developmental period (Beecher & Van Pay, 2021; Demir-Lira et al., 2021; Hoff, 2006; Suskind, 2015). In the 1960's Betty Hart, an education researcher, and Todd Risley, an applied behavior analyst, pioneered research on early language exposure. In classroom observations, they observed that students learning trajectories differed despite receiving the same instruction (Hart and Risley, 1995). At the time, researchers had started to design and implement early interventions to address the achievement gap and improve students' academic performance from low-income homes. Teachers in schools implemented early interventions to support 4- to 5-year-old children from low socioeconomic status (SES) families. Though student vocabulary, cognitive performance, and language abilities typically increased immediately following the intervention, the change in performance was only temporary and ultimately did not change the children's developmental trajectories (Hart & Risley, 1995). Assuming language learning trajectories were not only determined by genetic inheritance, Hart and Risley sought to expand interventions. They realized assessing the child's home learning environment was necessary to understand how to design better interventions that improve child language trajectories with sustained change.

In their landmark study, Hart and Risley (1995) determined how and when differences in expressive language trajectories occur. They recruited 42 families from various income levels and ethnic backgrounds with children younger than seven months old. They went into the families' homes and recorded "everything" for one hour, including all words spoken by adults (1995). The researchers observed the children monthly from about eight months old until they were three years old. After almost two and a half years of observation, all the children had learned to talk. However, like the classroom observations, the study results showed that children had differing vocabulary growth trajectories, and the growth rate positively related to the family's income level (Hart & Risley, 1995; 2003). Specifically, when Hart and Risley graphed the vocabulary trajectories by month, a noticeable gap emerged between high-achieving and lower-achieving children by two years of age. Specifically, children of high SES families demonstrated cumulative vocabularies of 1,116 words by three years old with a growth rate of 43 words per month. The cumulative vocabulary trajectories of high-income children were twice the growth of children of low SES families who demonstrated an average of 525 vocabulary words with an average growth of 20 words per month.

Hart and Risley (1995) graphed cumulative child vocabulary trajectories to depict temporal differences in child expressive language developmental trajectories, but child-level data could not explain why differences emerged. However, a potential cause for these differences was evident when observing cumulative graphs of adult language. In their study's most important finding, Hart and Risley found that the quantity of parent language spoken to children predicted the child's vocabulary growth. When graphed according to SES, children from high SES families experienced an average of 45 million words. Children from middle SES families experienced 26 million average words, and children from low SES families experienced 13 million average words. The average difference in the number of words between children from high SES families and children of low SES families heard by the time they were three years old was thirty million words, giving the landmark study the name "the Thirty-Million-Word Gap." Furthermore, the child's gender, the amount of money families had, or the caregiver's jobs did not predict the child's language trajectories. The quantity of language caregivers exposed their children to impacted child language trajectories (Hart & Risley, 2003; Suskind, 2015).

Although all children must have had the language experiences necessary to learn to talk, some children experienced greater quantities of language, which was associated with higher achievement (Hart & Risley, 1995). Ultimately, typically developing children acquire and match the amount of language their caregivers express, so talkative caregivers have talkative children (Hart & Risley, 1995). Children exposed to low amounts of language grow up to be adults who express low amounts of language, creating generations of speakers who express lower quantities of language.

Products of the Thirty-Million-Word Gap

Since Hart and Risley's publication in 1995, numerous studies have replicated and extended the original work and found comparable results that accentuate the importance of exposing children to higher quantities of language (e.g., Greenwood et al., 2011; Hoff, 2003; Murray et al., 2006). This line of research has influenced how the education field understands child development and has influenced policies related to supporting children from low-income backgrounds.

In response to the emphasis on the importance of child education and caregiver support prior to kindergarten, legislators expanded or developed several federal programs. In the wake of Hart and Risley's study, federal funding expanded for early education programs, such as Head Start, to provide greater opportunities for young children (Magnuson et al. (2004). Other programs, such as the Special Supplemental Nutrition Program for Women, Infants, and Children now focus on providing nutrition to low-income women and young children. The program also seeks to increase the quality of mother-child interactions to improve child development (Bolbocean & Tylavsky, 2021). Additionally, Geoffrey Canada developed a community-based intervention, Harlem Children's Zone, to improve the quality of early childhood environments for children of Harlem, New York (Canada, 1995; hcz.org). The success of Harlem Children's Zone informed the development of Promise Neighborhoods, an educational program aimed at supporting students' developmental and academic outcomes in low-income neighborhoods across the United States (MacAfee & Torre, 2015; see ww.promiseneighborhoods.ed.gov). Thirty-Million-Words is another community-based early intervention developed by researchers to improve children's developmental outcomes by increasing the amount of children's early language exposure, specifically in low-income areas (Suskind, 2015; Suskind et al., 2013; 2016; see tmwcenter.uchicago.edu).

Language Measurement in a Child's Environment

A child's language environment predicts their future achievement (Greenwood et al., 2011; Hart & Risley, 1995; Hoff, 2003). Therefore, measuring expressive language in a child's immediate environment is essential for the identification of children who are at risk of low quantities of language exposure, such as children with language delays or disabilities. The ability to measure a child's language environment could also be useful to measure changes in the child's language environment related to the intervention (Dykstra et al., 2012). Of the methods available to sample and record expressive language from a child's environment, many studies, including Hart and Risley's study, rely on written transcription of language captured on audio or video recordings and in-person observations. Researchers, educators, and engineers have recently developed a novel technology to facilitate language sampling, transcription, and data analysis (Xu et al., 2008).

Audio and Video Recording to Sample Language

Some barriers to current mechanisms to collect language samples are potential confounds and logistical challenges. Potential confounds include biases due to observation and contrived settings. The unfamiliarity of an observer, equipment, or contrived setting such as a room designated for research in a clinic or university setting could bias language samples. This bias is known as the Hawthorne effect (Dykstra et al., 2012; Trembath et al., 2019). Other biases may include observer bias and observer drift. For example, suppose the observer has a preconceived idea of family and child performance over time. In that case, the observer may record instances of language or interaction more conservatively or freely (e.g., observer bias). The way observers record instances of language or interaction may change over time (e.g., observer drift).

Logistical challenges include time, expertise, and cost. Human observers need time and expertise to schedule observations, observe and record data, and to transcribe and analyze reliable data (Dykstra et al., 2012, Trembath et al., 2019). A demanding part is scheduling observations around a family and the researcher's availability. To quote Hart and Risley, "[n]one of us [researchers] took a day of vacation for more than three years… [the caregivers'] schedules completely determined ours" (1995, p 41). The time it took Hart and Risley to collect all observations equated to 1,318 hours. Additionally, Transcription can quickly become overwhelming when observation durations are long, data collection is frequent, or observers collect data over long periods. It took three additional years after Hart and Risley collected the recordings to transcribe them before the language data could be reliably coded and analyzed. Finally, the expense of direct observation and human transcription can be costly due to personnel time, expertise, and equipment (Crowley-Koch & Van Houten, 2013).

Novel Technology to Sample Expressive Language

In response to Hart and Risley's study and the taxing nature of direct observation, a team of researchers, educators, and engineers developed a computerized language processing software to ease the language sampling process for researchers (Gilkerson & Richards, 2020). Language ENvironmental Analysis (LENA) technology, as Suskind (2015) used to measure language, is a “talk pedometer” that automatically measures expressive language in a child’s natural environment (Ford et al., 2008). LENA technology consists of the LENA Digital Language Processor (DLP) and LENA software. The LENA DLP is an audio recording device that fits into a small (8.56 x”5.56 x 1.27 cm, 56g) specially designed pocket on the front of a t-shirt worn by the focal child”(Ford et al., 2008). The audio recording device can record up to 16 hours of audio data. When a researcher uploads the data to a computer with LENA software, the software automatically analyzes the data. The LENA software further disaggregates the audio data for sound features to differentiate between adults, children, noise, or electronic sounds (Xu et al., 2008). Researchers can create automated reports with graphic displays of language measures for analysis (Xu et al., 2008). Some LENA measures include the quantity of male and female adult words (adult word count; AWC); the number of child vocalizations (CV), as measured by a consonant and vowel separated by 300 milliseconds; the number of conversational turns between the child and adult (conversational turn count; TC); and the number of vocalizations expressed by other children (Xu et al., 2008).

Initially designed for early language development researchers, LENA technology has developed additional programs that make the technology available to educators and clinicians, community-based programs, and parents. Programs include LENA SP, LENA Start, LENA Grow, and LENA Home (see www.lena.org/effectiveness/). Some benefits of automated data collection include the variety of variables that LENA can measure at one time, the ability to observe a child's natural environment, the absence of an unfamiliar observer, the reliability of the pre-programmed measures, the ability to analyze data upon data upload, and the ability to analyze day-long language samples. Because of these advantages, LENA has been instrumental in measuring language in the natural home and school environments of children with language delays and disabilities, for whom capturing the natural language can be challenging (Bak et al., 2019; Dykstra et al., 2012; Ganek & Eriks-Brophy, 2018; Trembath et al., 2019; Wang et al., 2017).

Natural Language Samples of Children with Autism Spectrum Disorder

A subset of children at risk of low language exposure are students with language delays and disabilities that affect language and communications, such as autism spectrum disorder (ASD). Researchers have documented children with disabilities, such as ASD, have fewer interactions with adults than their neurotypical peers (Bak et al., 2019; Dykstra et al., 2012; Haebig et al., 2013; Vigil et al., 2005; Warlaumont et al., 2014). ASD is a neurodevelopmental disorder marked by social communication deficits and restricted and repetitive behaviors (American Psychological Association, 2013).

The language profiles of young children with ASD vary widely, but researchers have demonstrated that children with ASD, like their typically developing peers, also benefit from greater quantities of language exposure (Dykstra et al., 2012; Haebig et al., 2013; Kasari et al., 2013). Many individuals with ASD will develop advanced vocal expressive abilities. However, approximately 30% of individuals with ASD will not develop verbal expressive language abilities by age 5, severely reducing their prognosis throughout their lifetime (Tager-Flusberg & Kasari, 2013). Unfortunately, researchers do not often assess the language development of children who exhibit low rates of expressive verbal language, such as minimally verbal children with ASD. Researchers may conduct less research with minimally verbal children because language acquisition researchers recommend assessing the language of minimally verbal children using language samples over standardized assessments, and the collection and analysis of language samples can be difficult (Bak et al., 2019; Dykstra et al., 2012; Tager-Flusberg & Kasari, 2013). An important implication of Hart and Risley’s study is that caregivers and adults can learn to talk more to children to improve their developmental outcomes with intervention. However, it is challenging to measure child language exposure in natural settings, such as home or school environments (Dykstra et al., 2012; Hart & Risley, 1995).

ASD is a neurodevelopmental disorder characterized by social and communication deficits (American Psychological Association, 2013). Recently, researchers have used LENA technology to analyze the expressive language of young children with ASD in relation to their environment (Bak et al., 2019; Dykstra et al., 2012; Trembath et al., 2019; Wang et al., 2017). Researchers have suggested that traditional standardized assessments may not accurately capture the expressive language abilities of young children with ASD (Dykstra et al., 2012). LENA technology offers researchers and clinicians some advantages to measure the expressive language of children with autism including the measurement of preverbal vocalizations, the ability to assess the child's expressive language in the natural environment, and the ability to concurrently assess adult-child interactions (Bak et al., 2019; Dykstra et al., 2012; Trembath et al., 2019).

Researchers have used LENA technology to assess the expressive language trajectories of children with ASD in school and early intervention settings and have found variable results between studies (Bak et al., 2019; Trembath et al., 2019). Additionally, studies varied in several ways including the setting and intensity of instruction provided to students, the ages of the students, and the expressive language abilities of students. The variability between studies makes it difficult for consumers of the research to draw conclusions on the use of LENA technology to depict the expressive language developmental trajectories of children with ASD.

The Present Dissertation

The present dissertation will focus on research that applies LENA technology to the assessment of language of individuals with language delays or at risk of developing a language delay. In previous systematic reviews of LENA (N=2), researchers have used LENA technology with populations who speak various languages, have a diverse range of abilities, and across a wide range of ages (Ganek & Eriks-Brophy, 2018; Wang et al., 2017). Both reviews identified gaps in the literature and suggested that future research incorporate more diverse populations, including children with expressive language acquisition disorders (Ganek & Eriks-Brophy, 2018; Wang et al., 2017), and for language acquisition researchers to conduct LENA research in applied settings to identify environmental characteristics that support expressive language development (Wang et al., 2017). The present dissertation fulfills the alternative dissertation criteria within the special education program, wherein the author writes three thematically linked but distinct papers as the main body, with an introduction (Chapter 1) and conclusion (Chapter 5) that connect the work as a whole. The author writes each of the middle chapters as a standalone paper. The following sections discuss the purpose of each chapter of this dissertation, present the related research questions and data analysis, and state the outlets planned for further dissemination.

Chapter 2: Systematic Literature Review

The purpose of Chapter 2 is to systematically review language acquisition literature that uses LENA technology and to identify information on study methodology, LENA technology implementation, and the use of novel variables derived from LENA in applied research. Meeting this purpose expands the current literature by providing information to future researchers on the use of LENA technology in application with individuals with language delays or who are at risk of developing language delays. The authors will conduct the systematic literature review according to the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) 2020 guidelines. Furthermore, the review will exclude technical reports of LENA features. It will describe the general approach of research teams who use LENA technology in their studies to measure expressive language. The authors will conduct the systematic literature according to the following research questions: (1) For what purpose is LENA technology used? (2) How frequently did researchers collect LENA recordings, and for what duration? (3) What LENA variables did researchers report in their research? (4) In what settings have researchers used LENA technology? (5) What LENA programs are present in research? (6) What populations is LENA technology used with? (7) What study designs did researchers use to evaluate the language environment measured by LENA technology? (8) To what extent did researchers report the reliability and validity of LENA technology in their studies? The authors will analyze data using descriptive statistics. The expected publishing outlet of the present systematic literature review will be the *Journal of Behavioral Education*. Recent publications of systematic literature reviews in the journal have summarized educational technology such as Headsprout, a computer-assisted instruction for early intervention reading skills (Rigney et al., 2020).

Chapter 3: Repeated Measure Design

The purpose of Chapter 3 is to use LENA technology to evaluate the expressive language trajectories of preschool-aged children with ASD who are receiving EIBI. The results of the study will extend the results of Bak et al. (2019) and Trembath et al. (2019) and demonstrate the use of LENA technology to take repeated measures in a clinical setting. Chapter 3 will consist of a secondary data analysis using LENA data collected across the school year in an EIBI clinic. The authors will analyze children's expressive language trajectories using multi-level modeling to answer the following research questions: (1) To what extent do children in EIBI demonstrate expressive language gains, as measured by LENA technology? (2) To what extent do subgroups, as determined by the Mullen Scales of Early Learning Expressive Language domain, differ in CV, TC, and VR? The expected journal for publication is *Autism* because of the journal's focus on the dissemination of autism and EIBI research and continued interest in publishing research on the trajectories of child expressive language acquisition precisely measured using LENA technology (see Bak et al., 2019 and Trembath et al., 2019).

Chapter 4: Practitioner Tutorial

The purpose of Chapter 4 is to introduce LENA as a behavioral observation measure to behavior analytic practitioners working with young children with ASD to learn how to use LENA technology as part of behavior analytic services to encourage practical use of LENA technology. The chapter will discuss considerations for using LENA technology with clients. Information will include which LENA programs are available for behavior analytic use with young children, how practitioners can use LENA technology in behavior analytic services, and considerations for practical use of LENA in behavior analytic services. Finally, examples provided throughout the paper will illustrate the use of LENA technology in behavior analytic practice to improve the language environments of young children. The expected journal for publication is *Behavior Analysis in Practice* because of its behavior analytic practitioner audience and emphasis on publishing tutorials with implications for application in clinical practice, such as tutorials on using Google G Suite for organization during remote teaching (Dubuque et al., 2021) and on graphing data in Microsoft Excel for clinical use (Chok, 2019; Vanselow & Bourrett, 2012; Watts & Stenhoff, 2021).

CHAPTER TWO: MEASURING TALK WITH LENA TECHNOLOGY: A SYSTEMATIC REVIEW OF THE LITERATURE

A child's early expressive language environment plays a vital role in the child's cognitive, language, social, and emotional development and can influence the child's academic achievement (Gilkerson et al., 2018; Gilkerson & Richards, 2009; Hart & Risley, 1995; Walker et al., 1994). Heterogenic child achievement upon grade school entry prompted Hart and Risley to determine variables that influence early child development. They noticed students performed differently despite receiving the same instruction in school. It was essential to identify what factors contribute to higher achievement rates because students who did not enter school with advanced academic abilities had difficulty catching up to their more advanced peers. The disparity in achievement may only increase as students' progress through school and limit opportunities for lower-achieving students. This disparity is known as an achievement gap (Halle et al., 2009). Identifying factors contributing to the achievement gap is critical to developing interventions to mollify the adverse effects of lower achievement.

Hart and Risley (1992; 1995) conducted a seminal study that observed expressive language trajectories of young children prior to entering elementary school. Their study was novel because they went into families' homes to observe, record, and analyze all language and interactions between the children and their family members. Hart and Risley video-recorded parent-child interactions of 42 families during monthly hour-long observations, and observations occurred from when the children were 7 to 9 months old until the children were three years old. The study's primary results demonstrated that children experience vastly different quantities of expressive language in their home environments that positively correlate with their expressive language development. A secondary result was that the amount of expressive language children experience was also positively correlated with the family's SES. Consequently, children who experience more expressive language in their home environments enter elementary school with more advanced expressive language abilities than children who experience lower quantities of language. The results of Hart and Risley (1992; 1995) have inspired the development of innovative technology and programs to measure and provide early intervention to children at risk of low language exposure (Greenwood et al., 2017).

Language Environmental Analysis

Language ENvironmental Analysis (LENA™) is a non-profit organization founded in 2006 with the mission to transform children's futures through early talk technology and data-driven programs (see www.lena.org/history/). A team of researchers, educators, and engineers developed LENA technology to record and analyze a child's expressive language environment automatically in response to research conducted by Hart and Risley (1992; 1995). The LENA digital language processor (DLP) is an automatic recording device that can record audio for up to 16 hours and captures a variety of environmental variables that contribute to a global understanding of a child's expressive language environment (Ford et al., 2008). A team of researchers, educators, and engineers initially developed LENA technology for researchers evaluating the expressive language development of preverbal children between 2 and 48 months (Gilkerson & Richards, 2009; Gilkerson & Richards, 2021). Language acquisition researchers have validated LENA technology with speakers of different languages and have used it with typically developing children and children with disabilities (Wang et al., 2017). In addition, to clinical research, clinicians and educators have used LENA technology in various applied settings, including classrooms and homes (Ganek & Eriks-Brophy, 2018). Two previous systematic literature reviews have summarized how researchers have used LENA technology (see Ganek & Eriks-Brophy, 2018; Wang et al., 2017). An important implication of both reviews was that LENA technology could have greater application in clinical practice to support child language acquisition.

Systematic Literature Reviews of LENA Technology

In 2017, Wang et al. published the first literature review summarizing the use of LENA technology in educational research between 2006 and 2015. Wang and colleagues conducted their review to describe how researchers have used LENA technology in research and identify gaps in the literature that could shape research agendas and increase evidence-based practice in educational or clinical settings, and specifically, in special education. Wang et al. examined participant characteristics (i.e., age, disability, and languages spoken) and whether researchers used LENA technology for assessment or intervention purposes. In their review, Wang et al. found that researchers had used LENA technology with various populations primarily for assessment of expressive language or of the language environment and as a tool for providing feedback to adults in a child's language environment about their own language levels. Implications identified by Wang and colleagues are for future studies to recruit multi-lingual participants, identify characteristics of environments that support child expressive language development, and evaluate the impact of electronic media exposure on child expressive language development.

Despite the contributions, Wang et al. has some limitations. Primarily, Wang et al. did not conduct the review according to any guidelines to systematize the review process. Guidelines, such as the PRISMA, are essential to use because researchers designed them to remove bias from the results and interpretations of the review by providing a transparent framework to report the purpose, methodology, and results of the review (Page et al., 2021). Additionally, the review summarizes information related to LENA technology published prior to 2016. LENA technology has advanced in the last six years and LENA has developed three additional LENA programs to measure the language environments of children in various settings by educators and practitioners. A review that includes more recent published findings could also yield information on the use of novel variables used in research developed from LENA technology. For example, Harbison et al. (2018) developed a measure of child vocal reciprocity that researchers derive from two LENA measures that may provide a better indicator of the quality of parent-child interactions than TC alone. Additionally, since the publication of Wang et al., LENA has increased in popularity worldwide and the scope of the review may be outdated.

Around the publication of Wang et al., (2017), Ganek and Eriks-Brophy (2018) conducted a literature review to examine how applied researchers have used LENA technology to disseminate the information about LENA to language acquisition researchers and specifically to speech-language pathologists (SLPs) to inform clinical practice. In addition to the variables extracted and analyzed by Wang et al., Ganek and Eriks-Brophy extracted information relevant to how prior researchers implemented LENA technology, such as the interval between recordings and the number and length of LENA recordings, and if the study included human transcription. Both Wang et al. (2017) and Ganek and Eriks-Brophy (2018) emphasize the need to expand LENA technology with educators and clinicians and recommend that future researchers include more diverse populations and implement LENA technology within applied settings to provide greater understanding of language acquisition across populations. An updated review may yield additional information that may inform future researchers how to use LENA technology to evaluate a child's language environment and inform practice to improve child development.

The Cochrane handbook for Systematic Reviews (Cumpston et al., 2022) reports that in a study of 100 systematic literature reviews, every 5.5 years was the median amount of time to update the review. A decision framework developed by Garner et al (2016) outlines factors that may impact a researcher's decision to update a review such as the pertinence of the research questions and development of new methods or development of innovative technologies to conduct the review (Cumpston et al, 2022). An updated systematic literature review on the use of LENA technology to measure environmental variables related to language development may be beneficial to language acquisition researchers because of the application of guidelines to systematize the literature review process and the recent developments in the LENA technology. Therefore, the purpose of the present paper is to systematically review the literature and identify information on study methodology, LENA technology implementation, and the use of novel variables derived from LENA technology in applied research. The authors will conduct the systematic review according to PRISMA 2020 guidelines. The goal of the present systematic literature review is to describe the general approach of research teams that are using LENA technology in applied research to evaluate individual outcomes and to describe the populations represented in the literature with the following research questions:

(1) For what purpose is LENA technology used?

(2) How frequently did researchers collect LENA recordings, and for what duration?

(3) What LENA variables did researchers report in their research?

(4) What settings have researchers used LENA technology?

(5) What LENA programs are present in research?

(6) What populations is LENA technology used?

(7) What study designs did researchers use to evaluate the language environment measured by LENA technology?

(8) To what extent did researchers report the reliability and validity of LENA technology in their studies?

Method

The present systematic review consisted of a primary search that included electronic databases and a search of the LENA Research Foundation Website. The authors screened titles and abstracts of articles found in the primary search for exclusion from the present review. Full texts of screened-in articles were located and further screened against the inclusion criteria. Finally, the first author conducted an ancestral search from the included articles to locate additional articles that met the inclusion criteria.

Search Strategy

The first author conducted the primary search guided by the PRISMA 2020 Checklist (see fig 1; Page et al., 2021). The authors searched the following online databases for relevance to education and child development: Education Full-Text, Medline, ProQuest PsychARTICLES, and PsychINFO. The authors customized database searches to limit the search to peer-reviewed articles written in English, published between January 1, 2004, to December 31, 2021, the dates between the founding of LENA and the date of the present review. The authors conducted record searches using the following Boolean phrases essential to this literature review: *LENA* and *Language Environment* Analysis* (Wang et al., 2017). Then, the authors searched the LENA Research Foundation Website for additional records. The first author exported all records identified to the reference manager Zotero (2017). The electronic database search yielded 255 records, and the LENA Research Foundation Website yielded 156 additional records, for a total of 411 records and 203 unique records after duplicates were removed. After screening for inclusion, the authors conducted an ancestral search of included records by screening the cited literature of the full-text articles that met inclusion criteria. One additional article was included in the final study from the ancestral search.

Identification and Inclusion of Studies

Authors included articles in the present review if the study reported data collected from LENA technology and analyzed the data in relation to features of the participant's environment. The authors excluded articles if 1) the study was conducted only to report the validity of technical features of LENA technology, such as studies comparing the vocalization counts obtained from LENA to human-coded vocalization counts of recorded audio to validate the use of LENA technology with a given population (see Cristia et al., 2020, 2021; Bak et al., under review); 2) if the study was validating the use of LENA with speakers of a specific language such as with Dutch speakers (see Bruyneel et al., 2021); or 3) if the study used the LENA DLP to record audio but did not use the LENA software to analyze the recordings and yield data on variables associated with LENA (Ganek & Eriks-Brophy, 2018). If a record included multiple studies, the authors assessed each study individually for inclusion in the present systematic literature review.

The first author screened the titles and abstracts of the 203 records to exclude studies that did not meet the inclusion criteria. The first author removed the records that unmistakably fit the exclusion criteria. The first author kept the records that did not fit the three exclusion criteria for a more careful review. 136 records were potentially relevant, and the first author downloaded the full-text reports to screen against the inclusion criteria. Figure 1 summarizes the results of the search and screening process.

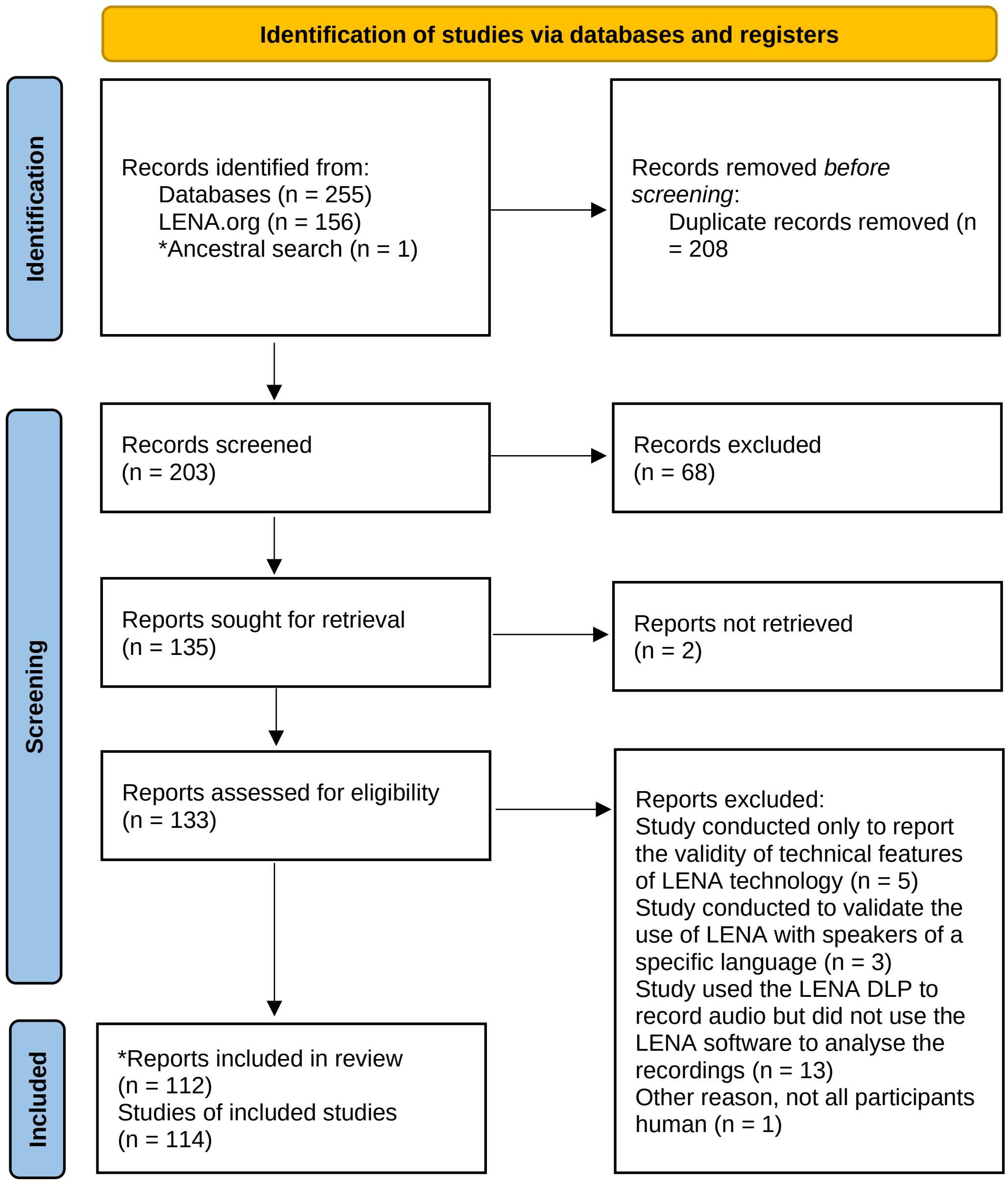

Figure 1. PRISMA 2020 Flow Diagram

Data Extraction

The first author developed an online coding spreadsheet in Microsoft Excel (2018) to collect data for each dependent variable. The coding spreadsheet consisted of four sections: 1) article identification, 2) participant characteristics, 3) study methodology characteristics, and 4) use of LENA technology. See Appendix A for specific codes used in the codebook for this systematic literature review.

Article Identifying Information. The coders extracted article identifying information, including the authors, year, and journal that published the article.

Participant Characteristics. Participant characteristics recorded by the authors from each study included the total number of participants who wore a LENA DLP, the number of total participants who were male, the reported ages of the participants, and any reported diagnoses or disability of the participants related to the purpose of the study. Next, the authors recorded the language spoken by the children or by the adults in the child's environment in the cases where the child was not yet verbal. Finally, the authors recorded the reported ethnicities and social-economic statuses of the participants in the study.

Study Methodology Characteristics. The authors recorded the research design of each study and if the study included an independent variable. The authors coded the purpose the researchers used the LENA technology, such as if the researchers used the LENA technology for assessment or feedback purposes (Wang et al., 2017). The authors recorded and coded the LENA variables reported in each study (i.e., AWC, CV, TC, other child vocalization, electronic noise) and coded if the study included a computed variable derived from LENA variables. The authors coded a study containing a derived variable when the researchers calculated a new variable from a numerical LENA measurement. If a study included a variable that the authors coded from the audio recording obtained by the LENA DLP or from a transcription of the audio recording, the new coded variable did not count as a derived variable because the LENA device was not necessary to obtain the audio recording or the coded measure. Additionally, the authors coded whether a study included procedures to ensure LENA technology's reliability and validity.

Use of LENA Technology. The authors extracted data to characterize the use of the LENA technology with participants. Data collected by the authors included the frequency of LENA recordings, the duration of LENA recordings, and the setting within which LENA recordings occurred. Finally, the authors recorded data specifying the LENA programs (e.g., LENA SP, LENA Start, LENA Grow, LENA Home, or not specified) used in the study.

Inter-rater Reliability. The first author trained a second coder to screen records and to extract data from each included study. The first author trained the second coder by describing the purpose of the systematic literature review, describing the coding process and each variable for data extraction (see below). The first author provided a model of how to code a record. Then, the second coder practiced extracting data and coding variables from a record, and the first author provided feedback on data extraction. The first author provided the second coder with 4 studies to practice screening titles and abstracts with the first author, and the second coder independently coded 4 records until achieving 90% reliability with the first author. The first author provided the second coder with 3 records to practice screening full text reviews with the first author, and the second coder independently coded 4 records until achieving 90% reliability with the first author. The first author provided the second coder with 1 study to code for practice with the first author that the first author collected from the studies included in the review, and the second coder independently coded 1 record until achieving 90% reliability with the first author. Additionally, the second coder reviewed 30% of all included articles (n = 34). The second screener did not identify any additional studies. The first author calculated the reliability between coders by tallying the number of codes where the coders agreed divided by the number of agreements plus disagreements, then multiplied by one hundred. Once the coders were reliable, the first author and second coder independently coded studies.

The first author assessed inter-rater reliability (IRR) between raters for all phases of screening and coding using Cohen's Kappa. The first author calculated IRR for the title and abstract screening for 30% (n = 61) of reports identified through the primary electronic database and LENA.org and was -0.41, indicating moderate agreement. The first author calculated IRR for full-text screening for 32% (n = 42) of reports and was -0.37, indicating fair agreement. Finally, the first author calculated IRR for coding of 32% (n = 37) of included studies and was 0.22, indicating fair agreement. The authors used Cohen's Kappa because of its ability to account for chance agreement between coders (McHugh, 2012).

Data Analysis

Prior systematic literature reviews on LENA by Wang et al. (2017) and Ganek and Eriks-Brophy (2018) used the descriptive statistics of averages, count, and percent data to summarize the findings associated with the research questions. The first author selected descriptive analyses to answer the research associated research questions because the questions are exploratory. Summarizing the current literature is necessary before researchers can conduct more advanced analyses to summarize the results.

Results

One hundred fourteen studies met the criteria for inclusion in this systematic literature review. The authors extracted and coded data to summarize the research included in this systematic literature review. The 114 studies are from 112 articles, with three articles reporting two studies (Beecher & Van Pay, 2021; Xu et al., 2018; Zimmerman et al., 2009).

Since 2004, the number of studies that have included LENA technology has steadily increased each year, with the majority (n = 22, 19%) published in 2020. See Figure 2. Appendix B summarizes the included studies and results, and Appendix C reports the citations of all 114 studies.

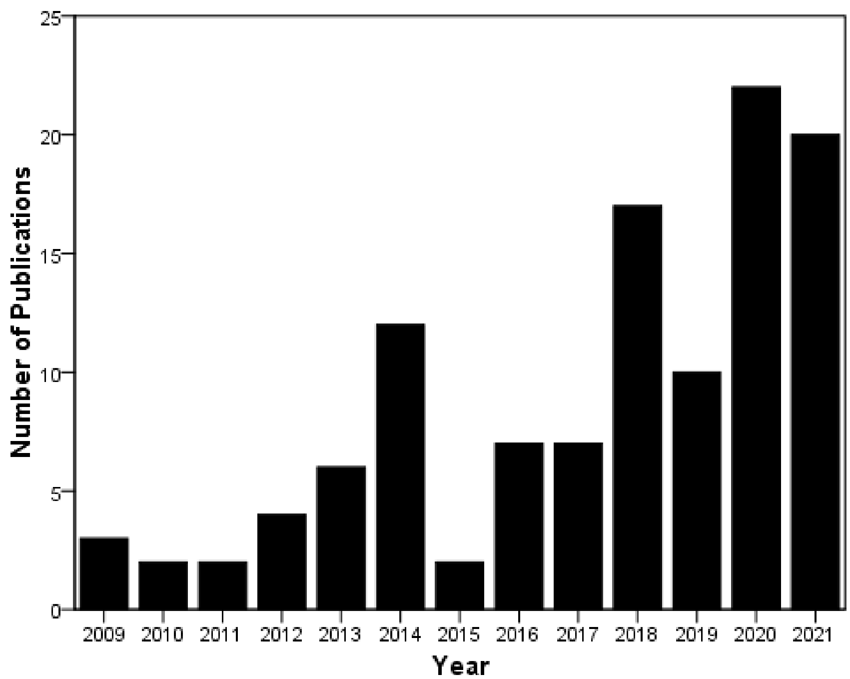

Figure 2. Number of Publications by Year

Purpose of LENA

Compared to using LENA technology for feedback purposes, most studies used LENA technology to assess a child’s language environment (n = 93, 82%). An advantage of LENA technology for researchers and clinicians is its ability to quickly assess a child’s language environment either in relation to other specific environmental stimuli or to gain a global understanding of the child’s use expressive language overtime in their natural environment. For example, Clemens & Kegel (2021) used LENA technology in relation to specific environmental stimuli (i.e., spontaneous and instructed activities, including book reading and toy play). And Johnson et al. (2014) used LENA technology to assess the expressive language environment shared between caregivers and infants during the child’s first seven months of life to gain a global understanding of the child’s language environment over time.

Twenty-one studies (18%) used LENA technology with the primary purpose of providing feedback to caregivers on specific variables in the child’s language environment. For example, Aragon & Yoshinaga-Itano (2012) used LENA technology to measure the TC exchanged between caregivers and children who were deaf or hard of hearing in Spanish-speaking families. The researchers then used the LENA data to provide feedback to the families as part of early intervention. Together, the families and early intervention teams developed strategies to increase the number of TC between caregivers and children. Similarly, researchers have used LENA technology as part of an intervention program to provide weekly feedback to caregivers on adult language and TC to improve children’s language environment over time (Suskind et al., 2013; Suskind et al., 2016).

Frequency and Duration of LENA Recordings

Thirty-seven studies (32%) measured the language environment from a single LENA recording. Three uses of single day-long LENA recordings in the present systematic literature review include the use of LENA technology to assess child expressive language performance in relation to another measure, such as a standardized measure of expressive language or measure of caregiver relationships, which may impact the child's language environment. These studies with multiple assessments compared the multiple measures to gain a better understanding of the intricacies of the child's language environment (n = 19). In one example of comparison across assessments, Marchman and colleagues (2017) collected single day-long LENA recordings to directly observe the quantity of language parents use around their children compared to parent reports of child language exposure in bilingual homes (Marchman et al., 2017).

A second use of a single day-long LENA recording was to compare the expressive language environments experience between two groups that differed on a predetermined characteristic to see how that characteristic is associated with differences in how the child experiences the language environment (n = 16). For example, Aragon and Yoshinaga-Itano (2012) used a single day-long LENA recording to assess the differences in language environments between Spanish-speaking children who are Deaf or hard of hearing with English-speaking children who were Deaf or hard of hearing. Aragon and Yoshinaga-Itano also assessed the differences in language environments between Spanish-speaking children who are typically developing and normal hearing and between English-speaking children who are typically developing and normal hearing. Aragon and Yoshinaga-Itano found that children who were deaf and hard of hearing in Spanish speaking homes experienced similar language environments to the children who were typically developing in English-speaking homes. Though there were many similarities, there were also differences between the four groups that would be important for delivering individualized and high-quality intervention. Aragon and Yoshinaga-Itano conclude that their study demonstrates the possibilities that LENA technology can provide to improve the quality of early intervention services to individuals with multiple disabilities and who are in Spanish-speaking households.

A third way researchers have used a single-day long LENA recording in the reviewed literature was to describe the language environment of a single sample of children (n = 7). For example, Nyberg et al. (2020) used a single day of LENA data collection to describe the language environment of Swedish children related to language development and Parikh and Mastergeorge (2018) used a single day of LENA recording to describe the language environment of children with Downs Syndrome. Both Nyberg et al. (2020) and Parikh and Mastergeorge (2018) discussed the wide variability in individual language environmental experiences. Parikh & Mastergeorge suggest the ability to depict behavioral phenotypes using LENA technology is invaluable to understanding the child’s language environment related to child developmental outcomes, including the relationship between child gesture communication and AWC (Nyberg et al., 2020).

Four studies in the present systematic literature review used a single-day long LENA recording with two of the three ways combined. For example, Adams and colleagues (2018) used LENA technology to assess full-term and pre-term child learning environments over a single day in relation to standardized measures of child language performance two months later. Ma et al. (2021) assessed the variability of child language environments in rural China and compared the measures in relation to child language skills.

Thirty-one studies (27%) measured the language environment using two LENA recordings. The majority (n = 18) of studies that measured the language environment using two LENA recordings used a pre-post study design and used LENA technology to assess change in the child language environment between two time periods (e.g., Brushe et al., 2020; Caskey et al., 2011, 2014; Dwyer et al., 2019; Pierce et al., 2021). Eight studies used two LENA recordings to assess the language environment over two consecutive days to capture variability in the language environment across two days (e.g., Romeo et al., 2018; Sultana et al., 2020). Five studies used a pre-test post-test design with LENA technology to measure a change in language environments over two non-consecutive days but also measured the language environment over two consecutive days at those two times (Benitez-Barrera et al., 2018; Benitez-Barrera et al., 2020; Christakis et al., 2009; Sacks et al., 2014; Swanson et al., 2018). The average number of days between LENA recordings of studies with two non-consecutive LENA recordings was 130.4 days (range, 3.5 to 365), or about one recording every four months.

Forty-six studies (40%) measured the language environment across three or more recordings. The average number of recordings per study with three or more LENA recordings was nine recordings (range, 3 to 47). The number of days between recordings did vary widely between studies. The average number of days between LENA recordings of studies with three or more LENA recordings was 33.07 (range, 1 to 168) days, or about one recording every month. For example, Gilkerson et al. recorded monthly for four (2017) and six months (2018), and Trembath et al. (2019) recorded monthly for ten months. However, several studies examined the language environment very frequently over three or more consecutive days (e.g., four days, Garcia-Sierra, et al., 2016; Ramirez-Esparza et al., 2014; six to eight consecutive days, Klein et al., 2018), and a few studies in this group recorded LENA data less frequently. For example, Ferjan Ramirez et al. (2020) recorded LENA data four times, four months apart, or every 112 days.

The average duration of LENA recordings reported in the present review was 11.08 hours (range, .17 to 16 hours). Of the 114 total studies included in the review, twelve studies did not specify a numerical duration of LENA recordings. However, eight of the twelve studies stated that researchers collected “daylong” recordings without specifying a duration. Based on other studies that used “daylong” and specified a duration of recordings, “daylong” may typically refer to 12-hours or longer (Clifford et al., 2021; Elmquist et al., 2021; Little et al., 2019; Ramirez et al., 2014; Reisinger et al., 2019; VanDam et al., 2012;2021; Wang et al., 2021).

LENA Variables

The most frequently measured LENA variables reported in the present review were AWC in 97 studies (85%), followed by TC in 87 studies (76%), and CV in 77 studies (68%). Researchers measured TV/electronic noise in 17 (15%) studies, female adult (near) in 16 (14%) studies, and male adult (near) in 14 (12%) studies. Researchers measured female and male adult (far) and silence across eight (7%) studies, measured noise (near) in six (5%) studies, and researchers measured noise (far) in five (4%) studies. Four (4%) studies reported vocalization duration, other child (near), and decibel level. Non-speech vocalizations, crying, other child (near), and overlap (near) variables were each reported in two (2%) studies. Finally, a single (1%) study reported on the duration of distant talk (Tulviste & Tamm, 2021), duration of TV/electronic (Liszka et al., 2019), child vocalizations (far), and other child (far; Benitez-Barrera et al., 2020), and overlap (far; Charron et al., 2016). The number of different variables in the literature has increased over time, see Figure 3.

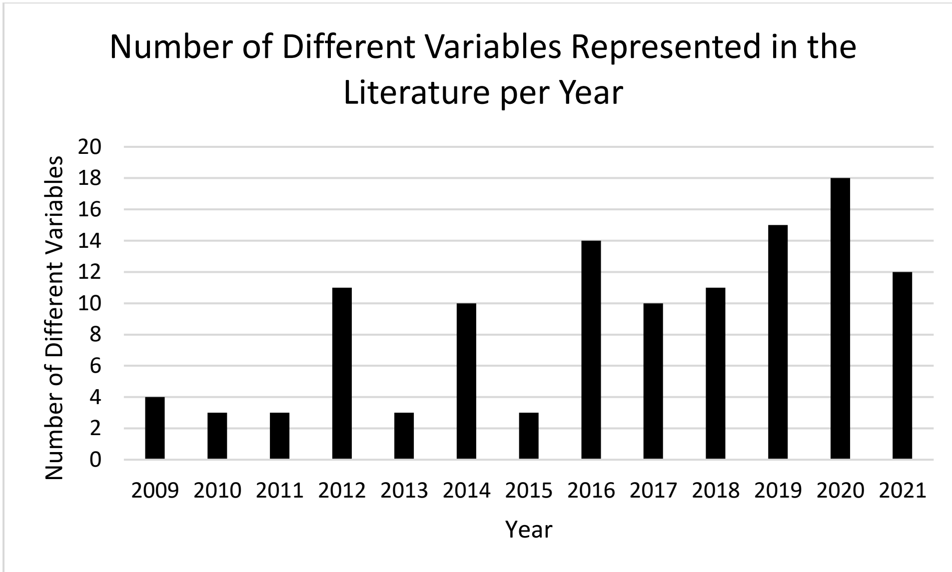

Figure 3. Number of Different Variables Represented in the Literature per Year

Ten (9%) studies included a variable that the researchers derived from LENA variables. For example, in addition to the maximum number of AWC, TC, and CV captured in one hour, King and colleagues (2020) computed the consistency of AWC and TCs because the cumulative availability of adults may indicate environment enrichment and impact child development. The researchers computed consistency by dividing the number of 5-minute increments with AWC and increments with TC by the total number of 5-minute increments in the recording. King et al. found infants who experience more consistent language in their first year of development had lower symptoms of psychopathology, independent from SES, measures of infant temperament, and maternal education.

Benitez-Barrera et al. (2020) recognize that high quality language environments are conducive to language and cognitive development. Characteristics of a high-quality language environment include child directed speech at good signal-to-noise ratios and high TC. Benitez-Barrera and colleagues computed weighted LENA variables from a signal-to-noise ratio computed from an online custom Matlab program. They found children with hearing often experience suboptimal listening conditions in their homes that can reduce learning opportunities. Benitez-Barrera suggests children with hearing loss should use assistive listening devices to improve signal-to-noise ratios at home.

The Setting of LENA Recordings.

The home environment was the setting where researchers used LENA technology to measure the language environment most often across studies (n = 97, 85%), followed by a classroom (n = 16, 14%) and the NICU (n = 8, 7%). Four studies (4%) obtained LENA data within childcare settings. For example, Soderstrom et al. (2013) measured the difference in adult speech and the number of children's vocalizations between daycare and home settings. Three studies (3%) obtained LENA data within the community across settings such as fast-food restaurants, "big-box stores", gas stations (Irvin et al., 2018), religious activities, restaurants, shops including grocery and big box stores, and outdoor settings, including parks and soccer fields (Little et al., 2020). Both Sulek et al. (2020) and Warlaumont et al. (2014) measured expressive language in clinical settings. For example, Warlaumont et al. used LENA technology to analyze naturalistic adult-child interactions that took place primarily in the home, but also during speech-language therapy for the sample of children with ASD (2014). Finally, Xu et al. (2018b) used LENA to measure expressive language in a research room to assess child vocalization features of children with selective mutism.

LENA Programs.

Researchers specified the LENA program in only five studies (4%). One study specified LENA SP (see Duncan et al., 2020) and four studies specified LENA Start (see Beecher & Van Pay, 2020; 2021a; 2021b; Elmquist et al., 2021). Though few studies identified the LENA program researchers used, 11 studies (e.g., Kristensen et al., 2020; Sulek et al., 2020; Swanson et al., 2019; Xu et al., 2018, studies 1 and 2 specified that the researchers used LENA Pro or LENA Pro prototype, that language acquisition researchers, educators, and engineers developed for use by researchers.

The Population of LENA Research Subjects.

Researchers identified a child as the primary participant in 63 (55%) of the studies and identified a family or parent-child dyad as the participant for 49 (43%) studies. Of the studies that included families or caregivers as participants, few studies (n = 32, 29%) included information on the gender of the participating caregivers. Of the 17 studies that included this information, most caregivers were female, with only 29% (n = 420) of caregivers identified as male caregivers. Of the total number of participants (N = 7341) in the present systematic literature review, 3988 (56%) of the child participants were female, and the average age of children was 2.41 years (range: 0.01 to 8 years). Finally, an older adult was the primary participant in the remaining two studies (1.75%). In both studies, LENA measured the auditory and social environment of older adults with hearing aids living in a mixed-income retirement community (Klein et al., 2018; Li et al., 2014). The average age of the adult participants in the two studies was 74.45 years (range: 64 to 91 years).

Ninety-six (84%) studies explicitly stated if a participant had a specific diagnosis that impacted expressive language development or was typically developing, accounting for 5,034 (69%) of all participants in the present review. Half of the participants (n = 3668, 50%) were typically developing across 53 (46%) studies. 20 (18%) studies identified participants as deaf/hard of hearing/hearing loss, which accounted for 425 (6%) participants. Researchers evaluated the language environments of participants with ASD in 9 (8%) studies, which accounted for 356 (5%) participants. Four (4%) studies included 203 pre-term infants as the primary participants, which accounted for 3% of the total participants in the present review. Two (2%) studies included 52 participants with Down's Syndrome, who accounted for 1% of all participants (Parikh & Mastergeorge, 2018; Thiemann-Bourque et al., 2014), and two studies (2%) included seven participants with a language delay, who accounted for .1% of all participants (Weil & Middleton, 2010; Irvin et al., 2017). Researchers across eight (7%) studies identified participants as children "at-risk" of developing ASD (n = 191; e.g., Seidl et al., 2018; Swanson et al., 2018), children "at-risk" due to low SES (n = 73; Liszka et al., 2020), children with a cleft lip (n = 20; Ha & Oller. 2021), older adults with no medical problems that would interfere with the use of the LENA DLP (n = 37; Li et al., 2014), children with a confirmed molecular diagnosis of full mutation Fragile X Syndrome (n = 9; Reisinger et al., 2019), and children with selective mutism (n = 12; Xu et al., 2018).

Languages Spoken by Participants. Seventy-nine percent (n = 90) of studies explicitly stated the primary language spoken by 6,090 (84%) of total participants. Fifteen of the 91 studies included bilingual speakers, which accounted for 6% of all participants (n = 439). Most participants spoke English (n = 5392 participants, 74.07% of total participants) represented in 79 studies, while four studies described 65 (5.46%) participants as speaking "non-English." Twenty studies identified 424 participants (5.78%) who spoke Spanish. Three studies identified a total of 69 participants (.94%) who spoke French, three studies identified 61 participants (.83%) who spoke Mandarin, and another three studies identified 123 participants who spoke Korean (168%). Thirty participants (.41%) spoke Chinese across two studies, 68 participants (.93%) spoke Vietnamese across two studies, and 180 participants (2.45%) spoke Swedish across two studies.

From the present review, participants also spoke Arabic (n = 8; Beecher & Van Pay Study 2, 2021), Estonian (n = 22; Tulviste & Tamm, 2021), Norwegian (n = 17; Kristensen, et al., 2020), Haitian Creole (n = 6; Romeo et al., 2021), Cape Verdean Creole (n = 2, Romeo et al., 2021), and German (n = 1, Benitez-Barrera et al., 2020). King et al. (2021) included participants who spoke a diverse range of languages: one participant spoke Cantonese, Danish, Polish, Hindi, and Tamil. In Elmquist et al. (2021), one participant spoke Russian, and in Donnelly and Kid (2021), two participants spoke Australian English. In addition to English and German, two participants also spoke American Sign Language (Benitez-Barrera et al., 2020). Finally, in a study by Beecher & Van Pay (2021), nine participants spoke an “other-not Arabic or Korean” language, 26 participants across five studies spoke a language identified as “other” (Beecher & Van Pay, 2021; Christakis et al., 2019; Elmquist et al., 2021; Trembath et al., 2019; Vohr et al., 2013), and it was “unknown” what language the 16 participants spoke across two studies (Caskey, 2011; Caskey et al., 2014).

Given a graphic depiction of the number of different languages represented in LENA studies by year, an increase trend in the number of languages is observed over time (see Figure 4).

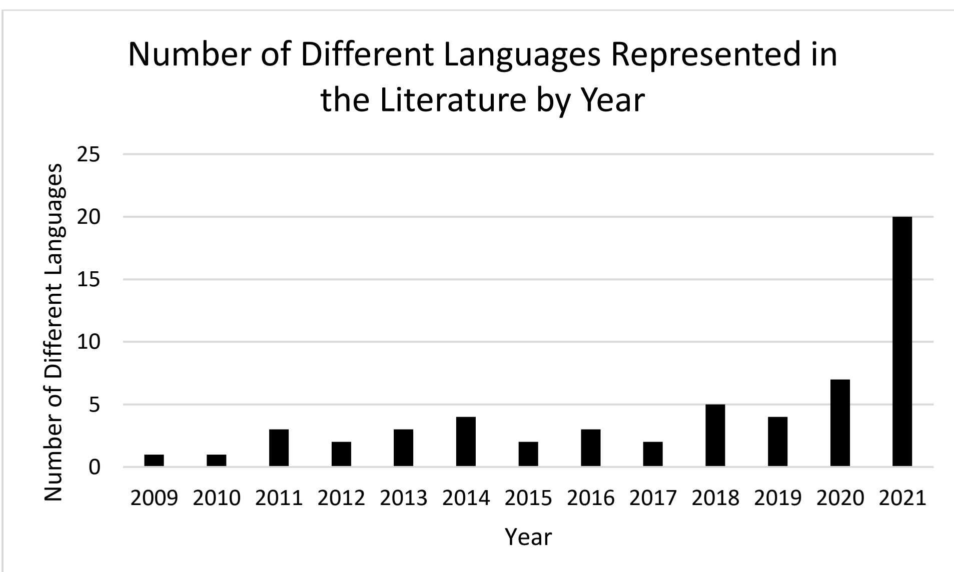

Figure 4. Number of Different Languages Represented in the Literature by Year

Racial and Ethnic Identities of Participants**.** Half of all studies in the present systematic literature review reported participant racial information (n = 57, 50%), representing 3960, or 54% of participants. Eight of the 57 studies (7%) explicitly differentiated and described participant ethnicity for 177 participants (2.4%) in addition to race. Fifty studies included 2317 or 31.64% of participants who identified as White or Caucasian, and 39 studies included 587 (8.01%) participants who identified as African American or Black. Five hundred sixty-nine participants (7.77%) identified as Hispanic or Latino/a in 33 studies, and participants who identified as Asian, Asian-American, or Pacific Islander made up 2.32% of the sample (n = 170) across 23 studies. Participants identified as Indigenous in seven studies and made up less than one percent of the sample (n = 17). Thirty-two studies combined the categories “multi-racial” and “other” (see Johnson et al., 2014); therefore, participants described as either represent 3.24% of the total sample (n = 237). In eight studies, researchers reported that 50 participants (0.68%) did not provide information regarding race or ethnicity. Five studies stated that the 13 (0.18%) participants’ racial identities were “unknown.” Readers should note that the authors based the reported percentages on a total population of N = 7385 instead of N= 7341 participants because some researchers reported that primary caregivers could select all demographic information that applied to their child and did not describe if any participants identified as more than one race or ethnicity. Therefore, the authors reported an additional 44 ethnicities than the total participants across four studies (Beecher & Van pay, 2021, Larson et al. 2020; Romeo et al., 2021).

Given a breakdown of the number of non-White participants included in research per year, the number of non-white participants appears to have increased in the last two years, see Figure 5. Additionally, the proportion of non-white participants to white participants appears to increase per year, see Figure 6.

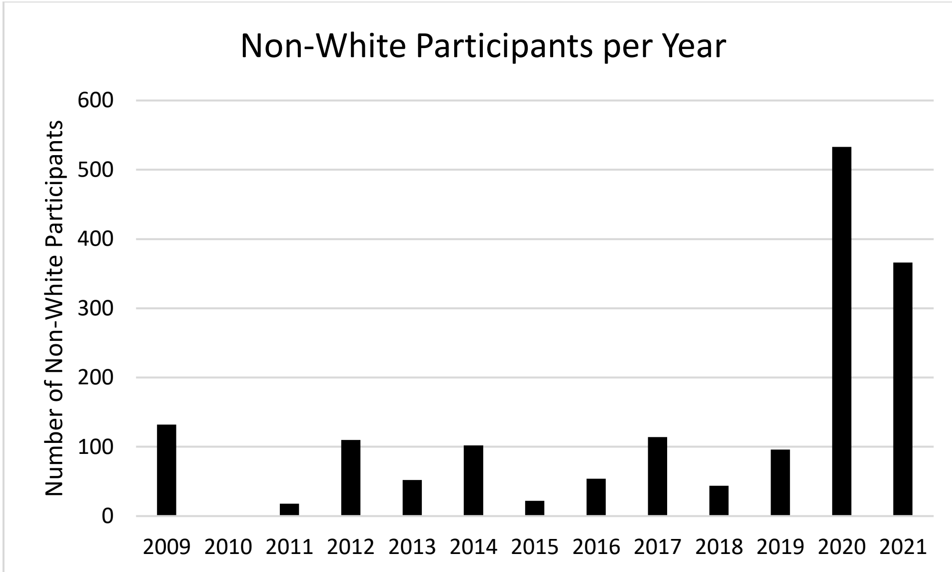

Figure 5. Number of Non-White Participants per year

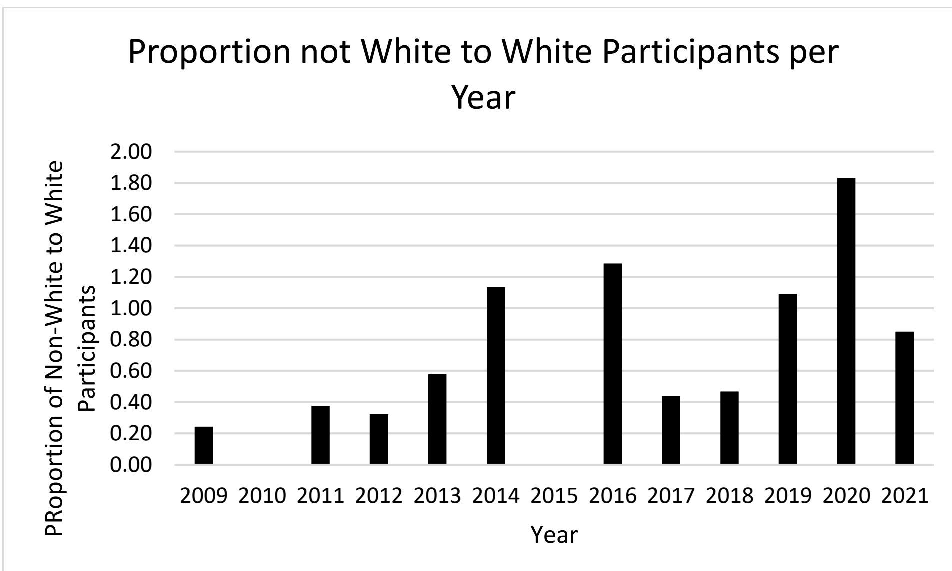

Figure 6. Proportion of Non White to White Participants per Year

Social Economic Status or Mother Education Level. Eighty-eight (77%) studies provided information on participants' social-economic status. Most studies reported maternal education level as a proxy for social-economic status (n = 77), while fewer studies reported information related to income level (n = 47). Thirty-seven studies included information on both income level and maternal education level. Of the 88 studies that reported the social-economic status of the participants, 72 studies included at least one participant whom the researcher identified as low income. How researchers determined low income varied between studies. For example, Brito et al. (2020) and Brushe et al. (2021) specified the mother's level of education attained and the number of mothers with less than a college degree to distinguish between "high" and "low" educated families. Researchers used the Hollingshead four-factor Index of SES to identify high and low-income families by Adams et al. (2018) and Ramirez-Esparza et al. (2014). While other studies, including Sacks et al. (2014) and Romeo et al. (2018), listed yearly income increments of participants and included some participants from a range of income levels, including families whose income was low and below the median income range for that region. Other studies specified that their participants were above or below the poverty line for the area (i.e., Gomex & Strasser, 2020) or below 200% of the federal poverty line (i.e., List et al., 2021). Finally, many studies included information related to if families reported receiving government assistance such as LINK/WIC (i.e., Leung et al., 2020), Medicaid (i.e., List et al., 2021; Vohr et al., 2013), and if children met criteria for free lunch, as documented through enrollment at a Head Start program or by a summer program for local children (i.e., Jackson & Callender, 2014). Figure 7 depicts the number of studies that specify including economically disadvantaged participants.

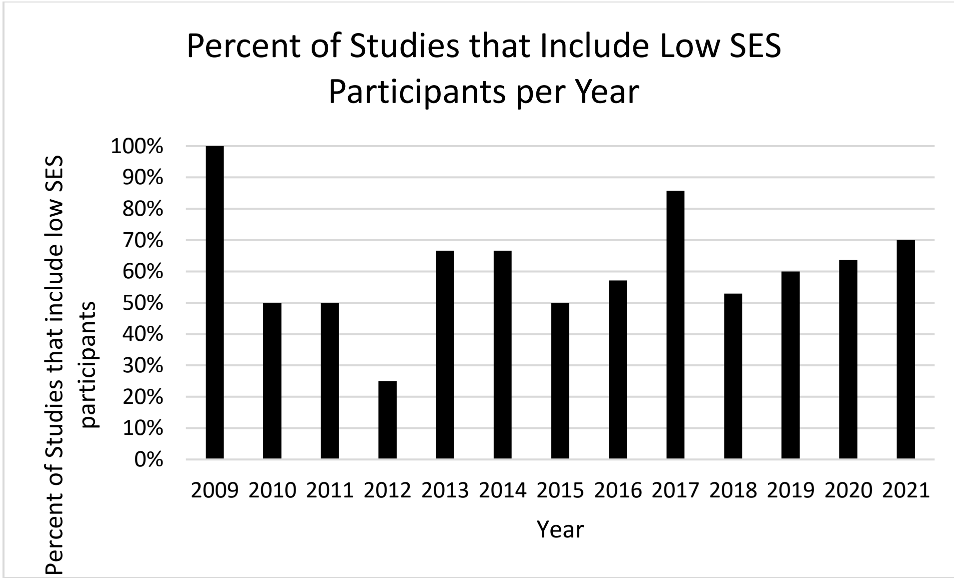

Figure 7. Percent of Studies that Include Low SES Participants per Year

Study Designs of Research using LENA Technology

Seventy-six (66%) studies in the present review included a research design description. Of the studies that reported a specific design, 68% of the research was observational research and used LENA technology to observe the language environment of the participant's natural setting (n = 52). Of the 76 studies that reported a research design, 21 studies reported using a longitudinal research design and 12 implemented a prospective cohort design. For example, Brushe et al. 2020 and 2021 used a prospective cohort design to evaluate the number of words caregivers expose their children to and the number of vocalizations children exhibit in their first year of life in relation to maternal education level. Eight studies implemented correlational methodology, eight studies implemented a cross-sectional design, seven studies implemented a randomized control trial, and three studies used a case study. Three studies used a pre-posttest study design, and three used a quasi-experimental comparison research design.

One study used a single-case experimental design. Kisshida and Kemp (2020) implemented an AB single case experimental design to demonstrate a relationship between a data-based feedback intervention and change in TC, as measured using LENA technology. Two studies used mixed methods (Ganek et al., 2019; Knight-McKenna et al., 2020). Both Burgess et al. (2016) and Pineda et al. (2017) used exploratory research design to understand the expressive language characteristics associated with home and preschool environments of children with ASD and the language environment in a neonatal intensive care unit (NICU), respectively. Van Dam and colleagues (2012) used a group comparison research design to compare the home language environments of children who are hard of hearing and the home language environments of children who have normal hearing. Klein and colleagues (2018) used a crossover design to describe the home language environment when hard-of-hearing children wore hearing aids compared to when they did not wear hearing aids. Xu et al. (2018) used an alternating block design to quantify children's expressive language with selective mutism in the presence of different people. Finally, Dykstra et al. (2012) conducted a descriptive study to describe the expressive language environment of children with ASD.

Reported Reliability and Validity of LENA Technology

Nineteen studies (17%) assessed the reliability of LENA in the study. All studies that assessed the reliability of LENA technology relied on human listeners to code LENA variables manually. For example, in Bak et al. (2019), a human listener transcribed and coded CV and TC from LENA audio recordings. Reliability assessment was essential because researchers had not previously used LENA technology to measure the language of minimally verbal elementary-aged children with ASD, the population assessed in the study. For this study, it was important to know how reliably LENA captured CV and interactions with adults to inform future researchers and clinicians using LENA technology with this population.

Researchers assessed the validity of LENA technology in nine (8%) studies. Studies assessed the validity of LENA technology by comparing the LENA measures against the measures of the expressive language of another validated measurement tool. For example, Gilkerson et al. (2017) validated the LENA measures of CV, TC, and AWC using correlations against other criterion assessments of child language development, including SLP-administered assessment and parent questionnaires. Greenwood et al. (2011) validated the LENA measures of CV and TC using correlations against the norm-referenced assessment of child language development, the PLS-4.

Discussion

The purpose of the present paper is to systematically review the language acquisition literature and identify information on study methodology, LENA technology implementation, and the use of novel variables derived from LENA technology in applied research to support the language acquisition of children with language delays or at risk of developing language delays. The following sections will discuss trends associated with the populations represented in research that uses LENA technology to measure outcomes related to participant expressive language environments and discuss how researchers have used LENA technology in the studies reviewed. The authors will discuss recommendations, future research, and limitations of the present systematic literature review.

The present systematic literature review included 114 studies that evaluated the language environment using LENA technology between 2004 and 2021. Overall, the research using LENA to evaluate the language environments of individuals has steadily increased, has included more diverse populations, and has included a greater variety of LENA variables over time. Published studies using LENA technology were highest in 2020. The increasing number of studies utilizing

LENA technology supports the need for conducting the present updated review as researchers generate new knowledge and apply LENA technology in new ways to support expressive language acquisition. If this increasing trend of use of LENA technology to measure the language environment continues, then it is important to continue reviews of the literature to provide updates going forward.

Participant Characteristics and Trends

The present systematic literature review addresses a limitation of the LENA research literature raised by Wang et al. (2017) and Ganek and Eriks-Brophy (2018) in finding that studies using LENA technology have included more ethnically diverse participants, including speakers of different languages. Although researchers have continued to recruit diverse participants, there is an ongoing need for researchers to continue seeking underrepresented populations in LENA research. The increase in the number of non-white participants in the last two years may be a product of the increasing trend of number of studies conducted using LENA technology to evaluate the language environment, see Figure 3. Additionally, there are many studies that did not identify participant demographics, so the readers need to interpret data with caution as it might not accurately depict the diversification of participant ethnicity per year. To gain a more accurate representation of the populations represented in research using LENA technology, future researchers need to provide participant demographic data.

Intentionally including and describing diverse populations in future applied research that uses LENA technology is particularly important given researchers conducted the Natural Language Study, that LENA norms are based on, in the United States with English-speakers and may differ in other countries with different cultures (Nyberg et al.,2020). Researchers should also include descriptions of the participants in applied research because practitioners using LENA technology may reference the research to inform practice.

In addition to the more detailed description of participant languages, the increase in the number of languages represented in the literature may indicate greater use of description versus use of nondescript non-English categories. Including descriptions of the language spoken by the individuals wearing the LENA DLP is important because variables such as culture, that people transmit through language, can influence the patterns of communication between speakers and listeners and it is important that researchers and clinicians recognize these differences to identify culturally relevant environmental factors to support expressive language acquisition of speakers of any language (Ganek et al., 2018). Researchers have validated LENA technology with speakers of five languages and, in addition to the greater number of studies using LENA technology over time, the increased language diversity may coincide with ongoing validity studies conducted on LENA technology with speakers of different languages (LENA, 2021). These data demonstrate the recent description and inclusion of participants of varied cultures who speak different languages. Future research should include more data from participants of varied cultures to better inform clinical practice to enhance the language environments of clients of these cultures.

Additionally, how researchers describe participant language in studies using LENA technology varied. In some studies, authors simply reported whether the participants spoke English or not English. Whereas in other studies, authors reported specific non-English languages spoken by participants. In future studies that use LENA technology, researchers should identify the specific languages spoken by the participants of the study. Identifying each specific language spoken by the participants will provide a more uniform way of reporting the languages across studies and will be more inclusive and less English-centric.

The majority (68%) of studies in the present review included economically disadvantaged participants. The high proportion of representation of economically disadvantaged participants in the studies included in the present review is not common in studies of child language development. For example, in a systematic review of language intervention research by Greenwood et al. (2020), they found that only 27% of studies included participants who were low-income, compared to the 68% of studies in the present systematic literature review. The high proportion of studies that included economically disadvantaged participants in the present review may have captured a trend that is unique to research that uses LENA technology to evaluate child language acquisition. This may be because researchers, educators, and engineers developed LENA technology in response to Hart and Risley's research that they conducted during the war on poverty to determine how to equitably serve lower income students who tended to perform lower upon entry to grade school than their higher income peers. LENA technology, like Hart and Risley's work, demonstrates we can enhance language environments to provide children with more learning opportunities prior to enrollment in grade school. It is important that researchers include participants from a range of income levels in their research to continue to identify factors that may be related to systematic barriers that economically disadvantaged communities face and develop data-informed interventions to support expressive language development of the community members.

Overall, future research should describe demographics of participants and continue to work to include participants with varying languages, ethnicities, abilities, and economic backgrounds to better understand language acquisition across populations. A more explicit description of participant demographics will help provide a more uniform and inclusive way of reporting information.

Environment and Variables measured using LENA Technology

An important finding of the present systematic literature review was that all but one study examined language in the natural environment. Rankine et al. (2017) discuss the importance of naturalistic observation to sample and assess language ability versus traditional language assessment conducted under structured or contrived settings that identifies or measures the extent of a language delay. Naturalistic language samples may be particularly important when assessing the language of individuals with language delays, such as minimally verbal children with ASD. Researchers typically conduct traditional language assessment under structured or contrived settings, which may not be as sensitive to small changes in language ability over time (Dykstra et al., 2012). This outcome supports a reported advantage of LENA technology, which is that researchers can use it to capture a more naturalistic sample of language. This advantage is related to the novel naturalistic observation procedures conducted by Hart and Risley. The ability to quantitatively measure expressive language, among other variables, without introducing observers is a unique feature of LENA technology. Future studies could continue to explore the language environment across settings, especially with the development of LENA programs designed to improve the language environment in community settings.

It is encouraging that research using LENA technology has diversified the number of variables reported in the literature because LENA technology provides researchers with a novel opportunity to simultaneously measure and analyze multiple factors. Prior to LENA's development, research has demonstrated these individual factors are related to expressive language development. The increasing diversity of LENA variables represented in research using

LENA technology shows an increase in the number of ways language acquisition researchers are analyzing the language environment. Assessing a greater variety of variables using LENA technology could lead to a better understanding of factors that foster expressive language acquisition in a variety of environments. For example, Aragon and Yooshinaga-Itano (2012) discuss the use of a combination of variables such as distant language (i.e., male word count (far), female word count (far), TV, noise, and silence) to caregivers to increase the quality of the language environments and by making speech more audible and directed toward the child. It is important that language acquisition researchers continue to include an array of variables in future research to better understand how these variables contribute to expressive language acquisition among different populations of children. In the future, a better understanding of how an individual child is experiencing their language environment as represented by a variety of variables may lead to a greater depth of knowledge in research and present practitioners with an opportunity to provide more individualized support and intervention to clients.

Implementation of LENA Technology

An important implication of results of the present review is that future studies should provide more detailed information about the implementation of LENA technology in research to improve communication of procedures to consumers and for future replication. Overall, few studies in the present review explicitly described the study design, the LENA program used to evaluate the language environments of individuals using LENA technology, or the reliability or validity of the LENA technology. Of the studies that reported a specific design, most of the research was observational research with repeated measures, which parallels Hart and Risley's original observational study and highlights an advantage of LENA technology for its ability to inconspicuously record and analyze day-long observations of a child's language environment.

Few studies identified the specific LENA program that researchers used to record environment data. Since 2016, LENA developed three LENA programs to accommodate different uses of LENA technology. For example, LENA designed LENA Start for educators to use within communities such as school districts, libraries, healthcare systems, and community-based non-profits to support families during a child's first years of life (2015). It is reasonable that studies published before 2015 (n = 29) used LENA SP, the LENA program initially developed for language acquisition researchers, because LENA introduced the other three LENA programs after 2015. The authors recommend that future researchers specify the LENA program used to collect language environmental data because of the increased emphasis on clinicians and teachers to use LENA technology.

Most studies in the present review did include the LENA recording duration, number of recordings, and interval between recordings, which is a critical procedural description that is necessary for replication and to inform future research using LENA technology. Overall, how often studies collect samples in the present systematic literature review varied widely. The present systematic literature review showed that the average interval between recordings often depended on the number of recordings included in the study. For example, studies that used a pretest-posttest design to evaluate an intervention measured the language environment using one recording every four months, on average, which differs from studies that measured the language environment with three or more recordings. Additionally, most studies stated the duration of recording times, however eight studies used the term "daylong," which may refer to a recording duration of 12 hours or longer but specifying the average duration in terms of hours would be helpful for future reviews, meta-analyses, and replication studies because the duration of the recording matters when determining the accuracy of the results. For example, the accuracy of the

AWC measure decreases from 98% to 83% when the recording time decreases from 12 hours to one hour (Warren et al., 2010; Xu et al., 2008; Zu et al., 2009).

It is important to note that there is no standard for how often or how many expressive language samples using LENA technology researchers should collect. In research studies, the research questions may guide this information, to an extent. However, in the present systematic literature review across similar studies, there were discrepancies. For example, to date, there are no recommendations for researchers to indicate if they should collect LENA data once a month, or for two consecutive days every three months to capture the subtle changes in child expressive language development. A benefit of the LENA technology is its ability to capture day-long audio recordings, however, it may be beneficial to collect and average the expressive language data over several consecutive days in case there are scenarios when a single day recording is not representative of the language environment. For example, during a LENA recording day in the home environment, it could be possible that during the prior night, a child was awake throughout the night, and the language levels the following day are lower than usual because everyone was exhausted. First, to address the lack of standard practices in the field of language acquisition using LENA technology to measure the expressive language environment, future research should make sure researchers explicitly state procedural information (Trembath et al., 2019). Secondly, future researchers should investigate the number of samples that researchers need to collect for reliable and valid measures of expressive language.

Reliability and Validity

Overall, studies reported good reliability between human listeners and LENA technology. Research has shown that the reliability between human listeners and LENA diminishes for shorter LENA recordings (Warren et al., 2010). Specifically, for AWC, the accuracy decreased from 98% to 83% when the recording length was 1-hr compared to the recommended 12-hr recording length (Warren et al., 2010; Xu et al., 2008). In Zimmerman et al. (2009), the researchers found good reliability between human coders and LENA. However, researchers also reported that transcribers identified that LENA erroneously coded television as adult speech in some instances and, at times, erroneously coded child speech as adult speech (Zimmerman et al., 2009). Kristensen and colleagues noted that CV may be less reliable in noisy environments with overlapping speech or when a female speaker uses a high-pitched voice (Kristensen et al., 2020). Given these reports, researchers may consider conducting reliability assessments within each research study, and in application, practitioners may consider repeatedly sampling the language environments. Repeatedly sampling the language environment within a short time frame could provide a representation of the variability of an individual's language environment.

Limitations

The present systematic literature review does have some limitations for consideration. First, because the purpose of the present systematic literature review was to systematically review language acquisition literature for applied research, the present review excluded technical reports because researchers did not conduct the study to report LENA outcomes in relation to the participants and their environment. Technical reports may have measured language environmental data using LENA technology that the authors excluded from the present review. Depending on purpose of future reviews, the authors may want to include these reports if the authors reported LENA environmental data such as TC exhibited by a sample of participants. Second, the present systematic literature review also excluded reports from non-peer review journals. There may be studies that use LENA technology and published in sources other than peer-reviewed journals, such as dissertations, which may contain information related to the purposes of this review. For example, a dissertation by Stolte published in 2017 used LENA technology to evaluate the implementation and outcomes of a Pivotal Response Training parent education program implemented within a community. Studies such as this may have relevant applications for future research and recommendations for practitioners relevant to another systematic literature review. Finally, the present systematic literature review only used descriptive statistics to analyze the results of the review. The use of descriptive statistics only summarizes the present results and limits the ability to draw inferences to other samples of studies using LENA technology.

Future Research

The results of the present systematic literature review yielded several recommendations for future research. First, in addition to providing feedback to caregivers, future studies that evaluate clinical language environments should consider using LENA technology to provide feedback to clinicians, such as educators, SLPs, and behavior analysts to increase the quantity of language clinicians expose to children in clinical settings (e.g., Christakis et al., 2019; Kisshida & Kemp, 2020). Wang et al. previously identified that assessment and feedback are two purposes for researchers using LENA. In the present systematic literature review, researchers used LENA technology only for assessment in the clinical setting and primarily used LENA technology for feedback purposes with caregivers in the home setting. Researchers could also use LENA technology to provide feedback to clinical staff to enhance the language environment in the clinical setting.

Future research using LENA technology in clinical settings should also consider evaluating the language development of students throughout intervention. For example, Bak et al. (2019) used statistical analyses to interpret the language trajectories of minimally verbal children in a public special education classroom over the course of a school year. Using LENA to repeatedly evaluate the language development of children in response to interventions could yield information about when to adjust the intensity or type of intervention.

In alignment with prior literature reviews summarizing research that uses LENA technology, future research that uses LENA technology should continue to work to include diverse populations, including children with expressive language acquisition disorders (Ganek & Eriks-Brophy, 2018; Wang et al., 2017), Additionally, when characterizing the demographics of study participants, it is important researchers specify the languages spoken by each participant and not use nondescript categories to describe languages spoken by participants other than English. Given the close relationship between language and culture, it is essential that future research carefully evaluate the difference in language environments between speakers of different languages because consumers of the research may need such information to provide culturally competent services. Providing recommendations to change the language environment while ignoring a family's primary language could be detrimental to the caregiver and practitioner or researcher relationship. Additionally, the results highlight the importance of future research to both explicitly state the race and ethnic information of participants and the need for future research to include more diverse populations in research.

Finally, procedural information related to LENA recording is important for replication purposes and determining the validity of the reported LENA measures. Future researchers should explicitly state this information. The authors recommend that future researchers specify the LENA program used to collect language environmental data because since its founding in 2004, LENA has developed programs (i.e., LENA Start, LENA Grow, and LENA Home) to support educators, families, and communities to enhance language environments to support literacy development in practice. Descriptions of these programs and discussion of how researchers are using these programs is important given the increased emphasis on clinicians and teachers to use LENA technology in practice (Ganek & Eriks-Brophy, et al., 2018).

Conclusion

The results of the present systematic literature review support prior literature reviews evaluating the use of LENA technology in research and advocate that future research include more diverse participants including speakers of diverse languages, expressive language abilities, and ethnic backgrounds. Results suggest that research using LENA technology is increasing and beginning to diversify, but more work to intentionally include participants of diverse backgrounds is necessary. The results of the present review also show that research using LENA technology to evaluate the language environments in applied settings has a greater representation of participants of low SES communities than most language acquisition studies. This may be because researchers developed LENA technology in response to the work of Hart and Risley, who conducted their research in response to the war on poverty. Research has also begun to evaluate language environments using a greater variety of LENA variables, which could lead to a better understanding of factors that foster expressive language acquisition in a variety of environments. The present systematic literature review contributes to the language acquisition literature by describing how research teams are using LENA technology in applied research to evaluate individual outcomes and by describing the populations represented in that research.

CHAPTER THREE: ANALYZING THE EXPRESSIVE LANGUAGE TRAJECTORIES OF CHILDREN WITH ASD RECEIVING EARLY INTERVENTION: A REPEATED MEASURE DESIGN

Autism spectrum disorder is a neurodevelopmental disorder marked by social communication deficits and restricted and repetitive behavior (American Psychological Association, 2013). The language profiles of young children with ASD vary widely (Kasari et al., 2013). Many individuals with ASD will develop advanced vocal expressive abilities, however, approximately 30% of individuals with ASD do not develop verbal expressive language abilities and will remain minimally verbal, despite intervention (Tager-Flusberg et al., 2005; Tager-Flusberg & Kasari, 2013). Early intensive behavioral intervention is a well-established treatment for young children with autism that has demonstrated to improve the expressive language abilities of young children with ASD (Fuller & Kaiser, 2019; Reichow et al., 2018; Trembath et al., 2016). Despite widely reported growth in child expressive language development, there is variability in how children with ASD respond to EIBI and some children may not demonstrate as much language development as other children receiving the same intervention (Klintwall, et al., 2015; Paynter, et al., 2018).

Clinicians often conduct evaluations of expressive language development in relation to intervention, including EIBI, using standardized assessments that assess a child's global skill level at the time of administration (Matson & Rieske, 2014). Because most standardized assessments are not instruments that clinicians can administer frequently (i.e., weekly, or monthly), repeated measures using standardized assessments may not be sensitive enough to capture subtle changes of specific skills over short periods of time, such as minute changes in the expressive language ability of a minimally verbal child (Matson & Rieske, 2014; Grazadzinski et al., 2016). A sensitive repeated measure of child expressive language could inform timely intervention decisions by measuring the rate (i.e., slope) of the child's language development associated with the current intervention program and adjusting procedures when a clinician does not observe adequate growth in a child's language trajectory. Therefore, additional expressive language measures that clinicians can administer frequently and can measure subtle language skills may be useful to capture the language development of children with ASD who will remain minimally verbal and not respond to intervention.

Researchers have proposed that computerized natural language sampling procedures are a powerful tool to measure a child's expressive language development over time (Bak et al., 2019; Heilmann & Miller, 2010; Pezold et al., 2020). The collection of frequent natural language samples during early intervention could yield vital information about a child's expressive language development associated with early intervention. The variety of variables that a researcher or clinician can collect simultaneously with computerized natural language samples can contribute to a more sensitive analysis of the child's language development in relation to the child's environment. In addition to the variety of variables collected, the automation of data collection and analysis make the data accessible to practitioners, researchers, and parents with minimal effort to yield data that is already in an easy-to interpret and usable format (Greenwood et al., 2018; Suskind et al., 2013). Collecting frequent computerized natural language samples can also minimize biases that are associated with standardized assessments or other measures that rely on observation. Biases such as the Hawthorne effect, observer bias, observer drift, the time and cost to observe discrete skills during observational assessment and the contrived nature of the scenarios set up to elicit opportunities for a child to demonstrate a specific skill can yield unreliable results (Dykstra et al., 2012, Trembath et al., 2019).

Researchers have identified LENA technology as a potentially useful tool to collect and measure frequent nature language samples of children with ASD during EIBI (Bak et al., 2019; Dykstra et al., 2012; Trembath et al., 2019). LENA technology consists of software and a recording device used to automatically capture and analyze natural language samples of young children (Gilkerson & Richards, 2009). A team of researchers, educators, and engineers developed LENA technology in response to the landmark longitudinal study by Hart and Risley (1992; 2003) that analyzed the quantity of language children experienced in their home related to the child's academic performance, vocabulary breadth and rate of growth, and IQ. LENA technology can expediate the intensive data collection and analysis process. Recently, researchers have used LENA technology to analyze the expressive language experienced and produced by children with ASD (Wang et al., 2017), and as a tool to measure the language trajectories of children with ASD over time related to their instructional environments (Bak et al., 2019; Dykstra et al., 2012; Trembath et al., 2019).

Dykstra and colleagues (2012) used LENA technology to analyze and describe the language environments of preschools educating 37 young children with ASD related to child characteristics observed from standardized measures. In addition to standardized measures of language, cognition, and autism severity, the language environmental data collected included rate of CV, rate of TC, and rate of AWC. Dykstra and colleagues collected data over the course of 2 days for approximately 3 hours per day, six months apart. The results of Dykstra et al (2012) demonstrate that children showed a significant increase in rate of CV after 6 months. The observed increase in CV was strongly correlated to a well-validated standardized assessment of language of preschool-aged children. These results suggest the standardized assessment and LENA technology captured similar information. The authors hypothesized the results were the product of a combination of gains in the children's development and the instruction in the self-contained special education classrooms. As a result, the authors concluded that LENA technology may be a useful tool to measure expressive language in school settings over a brief period (Dykstra, et al., 2012).

Informed by Dykstra et al. (2012), Bak et al. (2019) used LENA technology to measure the language trajectories of individual children with ASD in an elementary setting. Bak et al. evaluated the language trajectories of nine minimally verbal children receiving special education in elementary school with an average of 17 observations, each of which spanned the entire school day (i.e., 9:00AM to 3:40PM), over the course of a school year. The results of Bak et al (2019) demonstrated that minimally verbal CV varied across the school year. Unlike the small comparison sample that consisted of two verbal children diagnosed with ASD, the minimally verbal children's rate of CV and TC did not increase. Bak and colleagues concluded that minimally verbal children with ASD may require more intensive and high-quality instruction to facilitate language development than instruction provided in a special education classroom and that the measurement of individual child language with LENA technology could be a way to further individualize communication interventions.

The results of the unique use of LENA technology by Bak et al. (2019) to map the language trajectories of individual children with ASD raises questions for future research about the use of LENA technology to measure language development of children with ASD. Specifically, the authors were interested to know if more intensive instruction, than what was available in the public education settings that their participants were in, could promote the expressive language development of nonverbal children with ASD. The authors also questioned if LENA technology may be contraindicated for use with school-aged children and might only be appropriate for use with younger populations of children with ASD, as in Dykstra et al. Finally, the authors question if LENA technology can capture the potentially subtle language changes of individual minimally verbal children with ASD and if future researchers or practitioners could use child-level data to individualize communication interventions.

Trembath et al sought to extend the findings of Bak et al. and to address limitations of Bak et al related to child age and instruction. However, Trembath et al. focused more on the language trajectories of aggregated subgroup measures, whereas Bak et al focused on the trajectories of individual children. Specifically, Trembath et al used LENA technology to record and analyze language trajectories of 23 preschool-aged children with ASD who were receiving instruction in an early intervention center. In addition to the CV and TC measures, Trembath et al also evaluated child vocalization ratio (VR), or the proportion of child speech vocalizations to nonspeech vocalizations to potentially assess more subtlety in child language development. Trembath and colleagues conducted ten, three-hour monthly observations. The group partitioned the observations into subgroups based on performance on standardized measures of language, cognition, and ASD characteristic level upon entering intervention. The results of Trembath et al. found no relationship between child expressive language abilities at baseline and child language trajectories over time. Overall, the vocalization trajectories observed by Trembath et al. were nonlinear and highly variable, resulting in no significant change over the course of the school year. Their results align with Bak et al.'s group sample of minimally verbal children with autism.

The interstudy variability yielded by LENA technology to measure the language of individuals and groups of children with ASD over time requires additional research to better understand to what extent researchers can use LENA technology to inform language development of minimally verbal children with ASD. Like Bak et al. (2019), Trembath and colleagues (2019) observed that CV varied across the school year. Trembath et al suggest that the observed fluctuations in CV, as opposed to linear trajectories, emphasize the need to continue measuring frequent expressive language samples from children with ASD, especially under intensive intervention.

The observed expressive language fluctuations by all subgroups of children by Trembath et al are like those observed by Bak et al., who found child language trajectories of minimally verbal children were highly variable across the school year. However, Bak et al, observed an increase of expressive language trajectory for students with ASD with more advanced verbal abilities than the sample students who were minimally verbal, demonstrating that research has recorded significant growth of language trajectories for some children with ASD. The inconsistent level of measurement across studies limits our interpretation of expressive language trajectories of students with ASD. The question proposed by Bak et al. (2019) of whether LENA technology can capture the potentially subtle expressive language changes of individual minimally verbal children with ASD over a year of early and intensive intervention remains and requires additional research to answer.

Additional discrepancies between studies, such as differences in the environmental conditions and child age, also contribute to the limited conclusions that readers can draw from prior literature that uses LENA technology to measure the expressive language developmental trajectories of children with ASD. For example, Trembath et al reported child classrooms to have a 1:2 to 1:4 staff to child ratio (Paynter et al., 2018) and the participants in their study received a minimum of 20 hours per week composed of a combination of naturalistic teaching strategies across all school contexts (Trembath et al., 2019). Meanwhile, the children in the Bak et al. study were receiving instruction in a public elementary special education classroom with a much smaller student-to-teacher ratio.

Given these discrepancies between studies and the recent emerging research on the measurement of individual child expressive language developmental trajectories, additional research is necessary to evaluate the use of LENA technology to measure child expressive language developmental trajectories (Trembath et al., 2019). Thus, the purpose of the present study is to evaluate the expressive language trajectories of preschool aged children with ASD who are receiving comprehensive EIBI. Specifically, the present study will sample expressive language of minimally verbal children with ASD over the course of the year using LENA technology. Similar to methods established by Bak et al. (2019), the authors used LENA technology to measure changes in frequent day-long expressive language samples of individual children in an EIBI clinic throughout the year. Like Trembath et al, children will be preschool-aged children receiving a high-quality EIBI. In addition to individual child developmental expressive language trajectories, the authors will also analyze language trajectories according to subgroups determined by the Mullen Scales of Early Learning (MSEL; Mullen, 1995), as described in Trembath et al. (2019). The present study will seek to answer the following research questions:

(1) To what extent do children in EIBI demonstrate expressive language gains, as measured by LENA technology?

(2) To what extent do subgroups, as determined by the Mullen Scales of Early Learning Expressive Language domain, differ in CV, TC, and VR?

Method

Data source and sample

The authors conducted an observational study with repeated measures of naturalistic language data collected at a comprehensive EIBI center in this study. To acquire the recorded naturalistic language samples used in this study, a researcher visited each EIBI site once a month to distribute the LENA DLPs to each of the children. The author turned on the LENA DLP and placed it into the front pocket of a specially designed t-shirt that each participant wore when recordings occurred. The authors of the present study analyzed data from the full instructional day, like procedures in Bak et al. (2019), compared to the three hours of data that Trembath et al. (2019) analyzed. Children wore LENA devices for about 6.5 hrs between 9:00 in the morning until approximately 3:30 in the afternoon. At the end of the day, the researcher collected the LENA DLPs and turned them off to complete the day-long recording.

Comprehensive instruction emphasized natural environment training and behavior analytic programing for social, communicative, cognitive, adaptive, and play skills across all school settings including the self-contained classroom, inclusive preschool environment, playground, and hallway. The instructor to child ratio was 1:1 and instruction emphasized request training either using vocal verbal language or via picture exchange if a child could not vocally produce language as a primary component of initial intervention. For additional information on the early intervention program see Plavnick et al (2020).

The authors included all children who had a diagnosis of ASD, completed one year of EIBI, had permission to participate in research from parents, and had the minimum number of recordings in the study. Like procedures in Trembath et al. (2019), each child had to have a minimum of six LENA recordings throughout the year and the first LENA recording had to coincide with the administration of the MSEL. Of the 35 children who were eligible for inclusion into the study, the authors collected sufficient LENA observations for 31 children. Due to the nature of applied research, the authors excluded four children from the analysis. Reasons for exclusion include the child was enrolled late and the first LENA measure was not obtained within the month of the MSEL administration (n = 2), the child left the clinic before completing one year of intervention (n = 1), or there were insufficient LENA measures obtained throughout the duration of the year due the child being absent on the day LENA data were collected or data were not collected due to a snow day.

Apparatus

The instrument used to record natural language samples of children throughout their first treatment year was the LENA Digital Language Processor (DLP). The LENA DLP is a small (8.56 x 5.56 x 1.27 cm), 56 g audio recording device that can record up to 16 hrs of audio and fits into a pocket of a specially constructed t-shirt worn by the focal child (Ford et al., 2008). Researchers record audio from the child's natural environment with the LENA DLP, and when the researcher connects it to a computer with LENA software, the software automatically extracts data from the audio recording (e.g., CV, TC, speech vocalizations, and nonspeech vocalizations; Gilkerson & Richards, 2009). For analysis, the researcher specifies what length to segment data from 5 min increments, hourly, or larger intervals (Xu et al., 2008).

Measures

The outcome measures used in the current study include CV, TC, and the VR, all of which the authors obtained from full-day LENA recordings. Like the approach used by Trembath and colleagues (2019), the authors divided the present sample into three groups based on the

MSEL expressive language (EL) age equivalent scores at baseline to assess differences in trajectories across subgroups (Trembath et al., 2019).

Child Vocalizations. LENA technology counts CV when the child emits a vocalization consisting of a consonant and a vowel separated by 300-msecs (Xu et al. 2008). Vocalizations include words, babbling, and pre-speech communicative sounds, but exclude non-speech sounds such vegetative sounds and fixed signals from electronic devices.

Conversational Turn Counts. LENA technology counts TC when a child emitted a speech sound that followed by an adult's speech sound to which the child responded within 5 seconds. The LENA technology also counts a TC when the adult initiated, the child responded to the adult, and the adult to the child's speech sound within 5 seconds (Xu et al., 2008).

Vocalization Ratio. The VR is the proportion of the child's speech vocalizations to nonspeech vocalizations that the researcher computes from the duration of speech vocalization and the duration of nonspeech variables analyzed from LENA technology (Rankine et al., 2017; Trembath et al., 2019). The results of Trembath and colleagues (2019) suggest that the VR may encompass additional information regarding the quality, or flexibility and directness, of the child's speech compared to just the quantity of child vocalizations.

Standardized Assessment. The MSEL is an assessment of cognitive skill administered to infants and young children up to 68 months of age (Mullen, 1995). Unlike other assessments of intelligence quotient, the MSEL independently assesses a child's expressive and receptive language abilities and therefore may better capture the language abilities of children with ASD, who may have contradictory receptive and expressive language (EL) ability, compared to assessments that do not differentiate between language domains (Akshoomoff, 2006). The MSEL EL subscale measures the language a child can produce (Longard et al., 2017). Both the reliability and validity of the MSEL EL domain is high. The reliability of the MSEL EL domain is above .80 and correlates strongly with other language assessments scoring .72 with auditory comprehension and .80 with verbal ability (Mullen, 1995).

Procedures

To obtain language environmental data, the first author uploaded LENA audio recordings to a computer with LENA software. The first author analyzed the data and downloaded excel files that contained extracted data for all LENA variables for each child per observation. For the present investigation, the first author segmented the data into consecutive 5-minute intervals.

Data Preparation. The first author computed the rate per minute of CV and TC for each observation across the year as in Bak et al. (2019) and Trembath et al. (2019) to account for varying recording lengths. Using automated formulas, the first author calculated rates by transforming the child vocalizations and TC variable data listed in the excel file for each observation. Each cell corresponds to a 5-min interval of expressive language data obtained by LENA. The first author cleaned LENA data by removing any cells that did not contain a full 5 min (i.e., 300 sec) due to the first author turning the LENA DLP on or off within the 5-minute interval. Additionally, if the data yielded “00” across all expressive language measures for more than ten consecutive minutes, the first author removed those consecutive intervals of data because it indicated an error in measurement such as removing the LENA DLP and placing it outside the measurement range of the child. The first author computed the child VR by dividing the speech to nonspeech vocalization columns. Then, the first author averaged CV, TC, and VR data over the duration of the recording and divided by five to obtain rate per minute. The first author computed the child VR by dividing the speech to nonspeech vocalizations.

Data Analysis. The first author consolidated data from each observation and entered it into IBM SPSS [Version 25.0; IBM Corp, 2017; West, 2009]. Then the first author calculated descriptive statistics including the mean, median, range, and standard deviation for each LENA observation. To describe the overall child vocalization rate of the sample, the first author combined individual child vocalizations per observation and then computed the mean, median, range, and standard deviation. The first author repeated the process for TC and VR. To display the language trajectories of the children across the treatment year, the first author mapped the mean child vocalization rate per minute using a time-series line graph.

To answer the first research question, the first author applied a linear mixed model (LMM) to evaluate the change in CV, TC, and VR for the group of children receiving EIBI across a calendar year (Bak et al., 2019; Trembath et al., 2019). Applied psychological and behavioral researchers often use LMM to analyze longitudinal data because researchers can fit LMM when there are missing data, when the number of observations is not equal between subjects and/or occur at different days throughout the study duration, and accounts for within and between-subject variance (Ryoo, 2011; West, 2009). The fixed effect of the LMM was time. The random effect of the LMM was each child to account for the variability between children. The first author assessed the assumption of normality with Box plots, QQ-plots, and Shapiro-Wilks tests of normality assessed the distribution of observations prior to analyzing the data with the LMM (Lomax, & Hahs-Vaghn, 2012; Mertler & Reinhart, 2017). Shapiro-Wilks test of normality is an appropriate test of normality for analyses with a sample under 50 (Lomax, & Hahs-Vaghn, 2012). If data were not normal, the author transformed the child-level data, or identified an outlier and excluded it from the analysis.

To answer the second research question and assess differences in trajectories based on MSEL baseline scores, the first author grouped the individual child trajectories by MSEL tertiles (Trembath et al., 2019). The first author created time-series line graphs to depict the average language trajectories across the school year clustered by MSEL tertiles (Bak et al., 2019, Trembath et al., 2019). The first author conducted Eta correlations to determine the degree of relationship between the subgroups and across the mean CV, mean TC, and mean VR dependent variables. Eta correlations can determine the strength of a relationship between a categorical independent variable and a continuous dependent variable (Jones, 2019). The null hypothesis of the correlation is that there is no association between the two variables, as measured by η ($i.e., H_0: \eta = 0$; Jones, 2019). The interpretation of Eta Correlation Coefficients is the same as a Pearson Correlation Coefficient and as follows: 0.0 indicates there is no association, 0.01-0.19 indicates there is negligible association, 0.2-0.39 indicates a weak association, 0.4-0.69 indicates a moderate association, and 0.7-1 indicates a strong association (Jones, 2019).

To compare trajectories between tertile subgroups, the first author applied t-tests to compare the difference between the first and final LENA measures of interest (i.e., CV, TC, and VR). The null hypothesis of the t-test is that there is no difference between the two means, or the two means are equal (i.e., $H_0: \mu_1 = \mu_2$ or $\mu_2 - \mu_1 = 0$). The assumptions of t-test are: 1) the dependent variable is continuous and normally distributed, 2) there is independence of observations, 3) the independent variable is categorical with two categories (Lomax & Hahs-Vaughn, 2012; Mertler & Reinhart, 2017). The Shapiro-Wilks Tests of normality indicated mean CV first and final data were not normal distribution, therefore, the first author used a Wilcoxon-signed rank test to compare the means of CV and VR measures (Mertler & Reinhart, 2017). The first author calculated and standardized the mean first and final LENA measures to compare values between tertiles. Then the author plotted the mean standard measures by tertiles on a line graph.

Finally, the first author conducted an Analysis of Variance (ANOVA) to determine the extent that subgroups, as determined by the Mullen Scales of Early Learning Expressive Language domain, differed in CV, CT, and VR between mean first and final LENA measures. The ANOVA statistic assesses the difference between the means of continuous variables across three or more groups (Lomax & Hahs-Vaughn, 2012). In the present investigation, an ANOVA was chosen to assess the extent of mean change from first to final measures on CV, TC, and VR across the three subgroups factor, with the null hypothesis that all means are equal (i.e., $H_0: \mu_1 = \mu_2 = \mu_3$; Lomax & Hahs-Vaughn, 2012; Mertler & Reinhart, 2017). The three assumptions of an ANOVA are: 1) dependent variables are normally distributed, 2) there is homogeneity of variances, and 3) there is independence of observations (Lomax & Hahs-Vaughn, 2012). Tests of normality indicate that the mean change distribution of VR in subgroup 1 was not normal (W(11) = .774, p = .004). Therefore, the first author used the non-parametric equivalent to the ANOVA, A Kruskal-Wallis H Test, to evaluate the extent of difference of mean change CV, TC, and VR between subgroups (Lomax & Hahs-Vaughn, 2012).

Results

The first author collected a total of 208 LENA recordings from thirty-one children. Most children were as male (n = 24) with a mean age of 41.55 months (range, 25-56 months) at the time of the first recording. All children spoke English in the clinical setting and most children were from lower-income families, as determined by the conservative assumption that Medicaid families had lower household incomes than households with private insurance. Specifically, twenty-one children belonged to families receiving Medicaid and 10 children belonged to families with private insurance. The first author calculated MSEL Expressive language subgroup tertiles. Eleven children fit the first tertile subgroup with a MSEL age equivalent score between 3 and 14, ten children fit the second tertile subgroup with scores between 15 and 26, and ten children fit the third tertile subgroup with scores between 27 and 39.

The first author collected a mean of 6.71 (range 6 to 8 recordings) recordings from each child. The mean recording length was 6.4 hours, (range, 0.83 to 7.25 hours) and the first author analyzed a sum of 79,995 minutes (1333.25 hours) of language data. The sample child vocalizations per minute was 3.33 (range, 1.14 to 8.64) with a standard deviation of 1.36 vocalizations per minute. The sample TC per minute was 0.86 (range, 0.14 to 2.08) with a standard deviation of 0.39 vocalization turns per minute. The sample VR per minute was 1.78 (range, 0.33 to 7.96) with a standard deviation of 1.07 vocalizations per minute.

Changes in child vocalizations, turn counts, and vocalization ratios over a year

The first research question was, *to what extent do children in EIBI demonstrate expressive language gains, as measured by LENA technology?* To answer the first research question, the results of the LMMs demonstrated that children statistically significantly increase child vocalizations and conversational turns across the school year. Specifically, child vocalizations per minute did statistically significantly increase over time ($\beta = 0.07$, standard error (SE) = .03; $t(202) = 2.29$, $p = .023$), see Figure 8. Conversation turns per minute also demonstrated a significant increase over time ($\beta = 0.02$, standard error (SE) = .01; $t(206) = 3.66$, $p = .000$), see Figure 9. Alternatively, time did not demonstrate significant effects for VR ($\beta = 0.04$, standard error (SE) = .02; $t(204) = 1.63$, $p = .10$), see Figure 10.

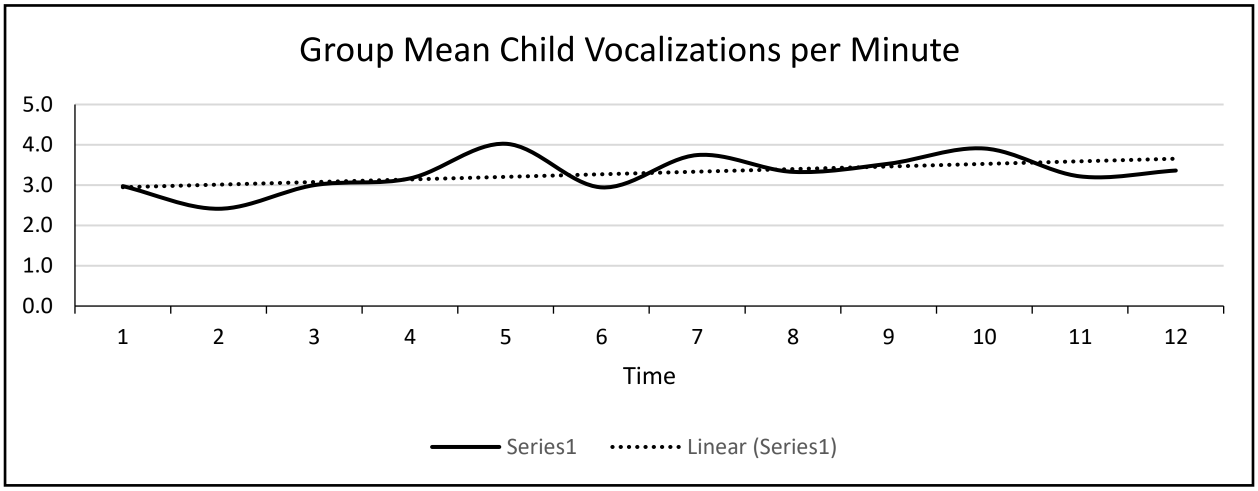

Figure 8. Mean Child Vocalizations (CV) per Minute.

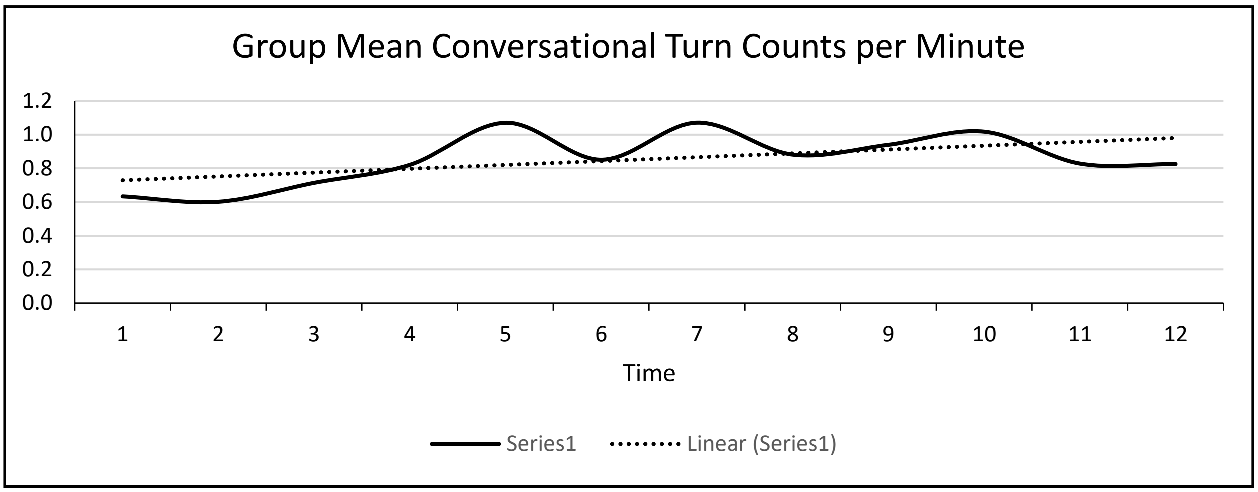

Figure 9. Mean Conversational Turn Count (TC) per Minute.

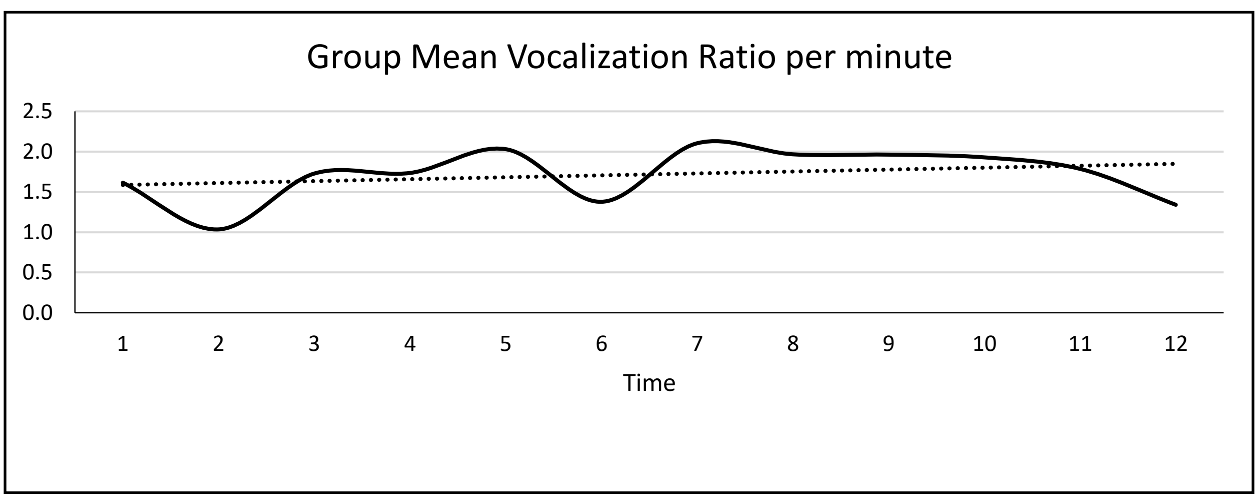

Figure 10. Mean Vocalization Ratio (VR) per Minute.

Child language trajectory based on subgroups

The second research question was, *to what extent do subgroups, as determined by the Mullen Scales of Early Learning Expressive Language domain, differ in CV, TC, and VR?* To answer the second research question, a Kruskal-Wallis H Test, a non-parametric ANOVA was conducted to assess the extent that subgroups differed between mean first and final LENA measures on dependent variables of interest. Before an ANOVA could be conducted, eta correlations were first conducted to determine the degree of relationship between the subgroups and across the mean dependent variables, a necessary step before answering the research question before conducting an ANOVA. Together, the results of the eta correlations and the ANOVA suggest subgroups differ throughout the year but make equal gains across the year in response to EIBI. Specifically, Eta correlations demonstrated a moderate positive relationship between the LENA variables of CV, TC, and VR and the three subgroups. Specifically, the Eta correlation between CV and each of the subgroups demonstrated a positive relationship ($\eta(35) = .555$). The results demonstrate a moderate positive association between TC and each of the subgroups ($\eta(35) = .441$), and the results showed a positive moderate correlation between the tertiles and VR, ($\eta(35) = .607$). The authors reject the null hypotheses that there are no relationships between subgroups and CV, TC, and VR.

Results of the paired sample t-tests the first author conducted to compare trajectories between tertile subgroups indicate the mean final LENA measures were statistically significantly different from the mean first LENA measures and the authors reject the null hypotheses. There was a statistically significant difference between the mean final CV ($M = 3.43$, SD = 1.36) and the mean first CV ($M = 2.91$, SD = 1.26) after receiving EIBI $Z(30) = -1.99$, $p = .046$. Mean final TC ($M = .86$, SD = .39) and the mean first TC ($M = 0.63$, SD = .310) were significantly different *t(30)* = 3.32, *p* = .002. Finally, mean VR at the beginning of EIBI (*M* = 1.61, SD = 1.48) was statistically significantly different than mean VR at the end of EIBI (*M* = 1.99, SD = 1.07), *Z(30)* = -2.57, *p* = .010.

The results of the Kruskal-Wallis H Test demonstrated that subgroups were not statistically significantly different across CV ($\chi 2(2) = 1.152$, $p = .562$), TC ($\chi 2(2) = .268$, $p = 0.875$), and VR ($\chi 2(2) = 2.2118$, $p = 0.330$), therefore the authors retained the null hypotheses. Mean CV, TC, and VR per minute by tertile subgroups across the year are depicted in Figure 8, Figure 9, and Figure 10, respectively.

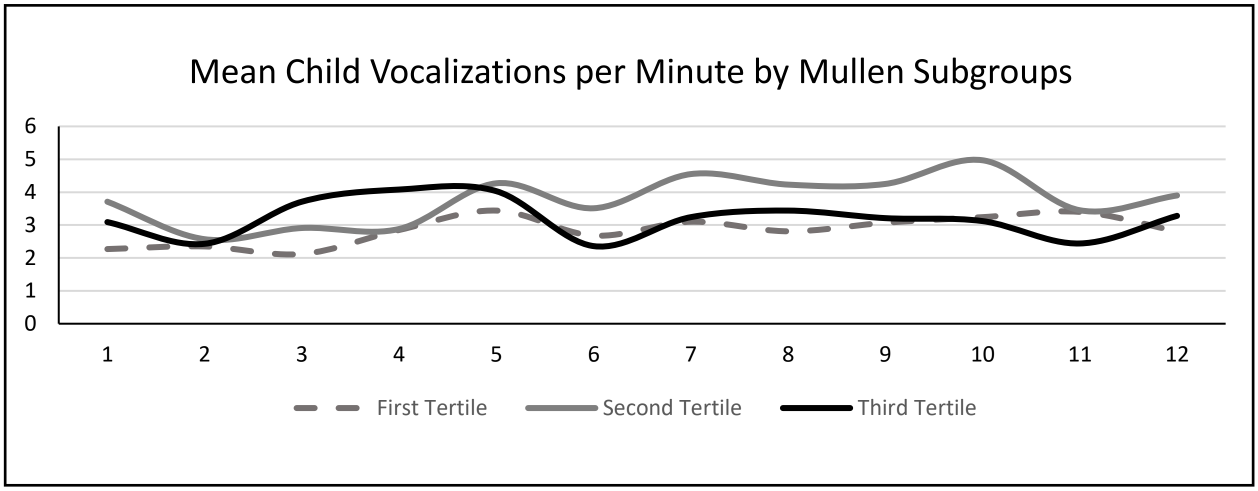

Figure 11. Mean Child Vocalizations (CV) per Minute Grouped by Subgroup.

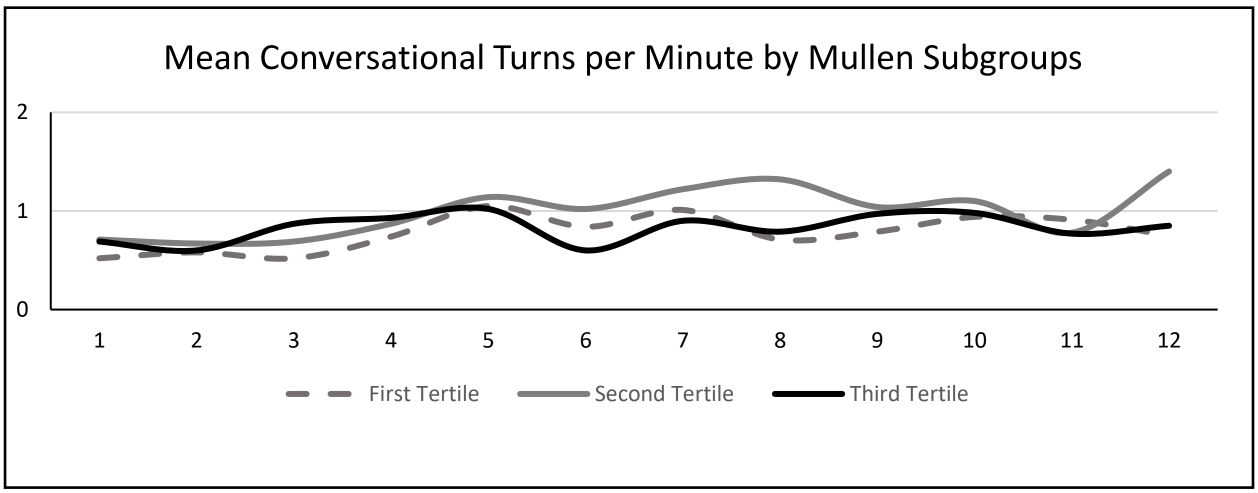

Figure 12. Mean Conversational Turn Counts (TC) per Minute Grouped by Subgroup.

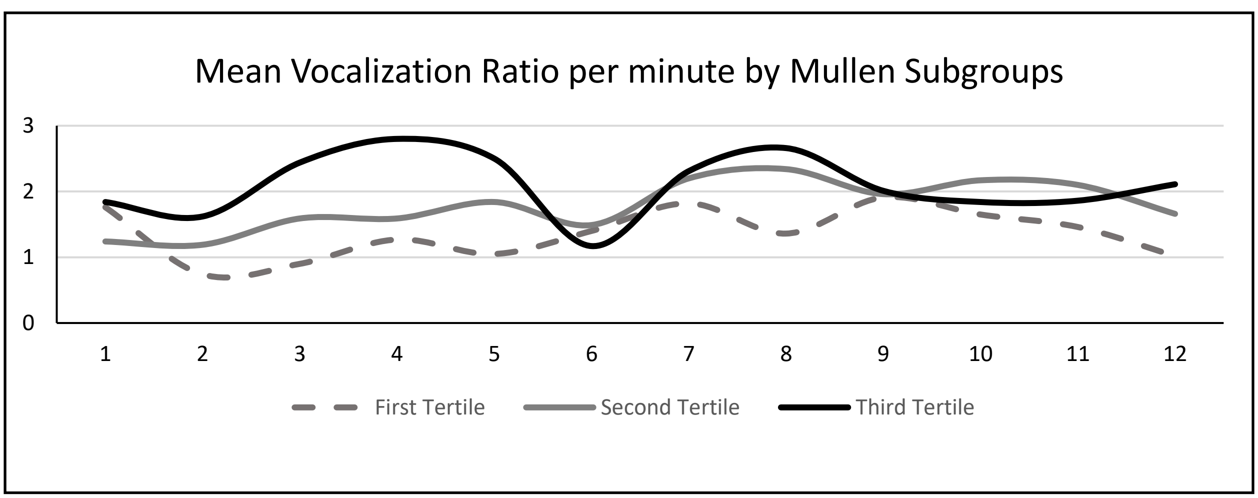

Figure 13. Mean Vocalization Ratio (VR) per Minute Grouped by Subgroup.

Discussion

The purpose of the present investigation was to evaluate the expressive language trajectories of minimally verbal preschool aged children with ASD who are receiving comprehensive EIBI. Specifically, the authors analyzed LENA data related to CV, TC, and VR at the group level. As a group, the children receiving EIBI in the present study demonstrated variable but statistically significant change in CV (standard deviation range .35 to 2.0) and TC (standard deviation range .11 to .58), but no statistically significant change in VR (standard deviation range .13 to 2.2). These results are consistent with Trembath et al who also found significant change in group CV and TC, but not VR.

These results differ from the children with ASD who were minimally verbal in Bak et al. (2019) who did not demonstrate an increase in either CV or TC rates over time. The increase of CV and TC observed in the present study could be a result of the more intensive education that clinicians provided to the sample of children in the present analysis like the instruction provided to the minimally verbal children in the early intervention setting by Trembath et al. (2019). Bak and colleagues theorized that the sample of minimally verbal children in her study might not have been receiving the extent of educational support that the sample requires and would have benefitted from additional instruction and from instruction in augmentative and alternative communication (AAC). The results of analyses of the present study support the conclusion that minimally verbal children can benefit from more intensive services, such as those provided in EIBI.

Whole Sample Expressive Language Trajectories

The results demonstrated statistically significant changes at the group-level analyzing change of CV and TC over time, and, using visual analysis, most children demonstrated highly variable increasing trajectories, especially on TC and VR, see individual child graphs depicting change in mean child vocalizations and mean turn counts in Appendix D. These results align well with the sample of minimally verbal children observed by Bak et al. who found few individuals made significant changes in either CV or TC across the school year. Bak et al. compared the language trajectories of the minimally verbal sample to the results of two comparison verbal students with ASD and both demonstrated significant increases in CV and TC over time (Bak et al., 2019). These results support a conclusion made by Bak et al. (2019), that inferences made at the group-level could overestimate the effect of the intervention when researchers do not also analyze the individual child-level trajectories. An analysis of the effects of the intervention at the individual level could help to communicate the interpretation of the results more clearly (Estrada et al., 2019).

It is also interesting to note that the observed increases in CV across individual child language trajectories is particularly interesting given services in EIBI focus on reduction of vocal verbal stereotypy with an emphasis on teaching functional language. The observed increase in CV trajectories suggests children may be demonstrating increases in functional language.

Difference Between Subgroup Expressive Language Trajectories

Visual inspection of the time-series line graphs depicts subgroups with trajectories that overlap and vary across the year. These results are like the results of Trembath et al. and Bak et al., who observed a waxing and waning of expressive language trajectories, compared to a uniform increase in rate of CV, TC, and VR. These results further support the value of using repeated measures to measure the change in expressive language trajectories over time instead of using single measures before and after intervention (Bak et al., 2019; Sandbank & Yoder, 2014; Trembath et al., 2019).

In the present analysis, the results of the Eta correlations demonstrate that the average rates per minute of CV, TC, and VR increase as the expressive language ability, as determined by subgroup, moderately increase. The moderate positive relationships suggest that the subgroups may demonstrate differences in child expressive language trajectory. The positive moderate relationship between CV and expressive language ability suggests children who have greater expressive language abilities upon entry to EIBI expressed greater quantities of vocalizations and conversational exchanges and had the greatest ratio of meaningful speech to non-speech vocalizations throughout the year than children with lower expressive language abilities upon entry to EIBI. These results align with the results of Trembath et al. that showed children with greater expressive language abilities at the start of early intervention showed the highest vocalizations and the lowest proportion of speech to non-speech vocalizations across the school year.

Using visual analysis, across the three LENA measures, VR is the measure where the tertiles appear to be the most distinct in the present analysis. Though all independent variables demonstrated a moderate and positive relationship with the subgroups, the relationship between VR and the subgroups was greater than CV and TC. These results support the hypothesis that VR could be a more subtle measure of child expressive language development for children with more severe language impairments.

The difference between first and final standardized language measures across subgroups observed was statistically significant. There was no difference between subgroups within each independent variable. Therefore, though all subgroups demonstrated significant change across a school year, results show no difference between the trajectories of children with low, moderate, and high expressive language abilities, as measured by the MSEL, upon entry to EIBI. It is possible that differences in expressive language trajectories by subgroups may be evident after a longer duration of intervention, however given the one year of data, the results suggest all subgroups show a similar increasing trend and EIBI could have an equal benefit, in terms of expressive language growth, for children of all expressive language levels. The variability observed within the sample, and even within the subgroups, further supports the usefulness of looking at individual child trajectories, when data are available, to better understand the results of the intervention (Bak et al., 2019).

Limitations and Future Directions

There are several limitations of the present investigation that are worth noting. First, the present investigation took place under intervention conditions in a clinical setting and readers cannot generalize the results and conclusions from the present investigation to the behavior of the children outside of the clinical setting because the intervention could skew the results. For example, in intervention, it may be part of a behavior intervention plan to redirect stereotypic behavior under specific conditions when it interferes with learning. The reduction of stereotypic behavior could inflate the VR measure by decreasing the number of non-speech vocalizations.

Second, the data in the present analysis are highly variable, which limited the conclusions researchers can draw from the results. Future research could include additional measures of factors with low multi-collinearity that influence the expressive language data yielded by LENA technology throughout the year and control for them in the analyses. For example, an important factor that future researchers may consider is the behavior technician working with the child on the day of the LENA recording, as the primary adult communication partner.

Finally, LENA technology is only capable of analyzing predefined quantitative data to characterize the expressive language of an individual, which limits the ability to conclude what a child was saying throughout the duration of the recording and limits the conclusions that researchers can draw from the results. Research teams who use LENA technology widely acknowledge this limitation in the analysis of the expressive language performance of children (Benitez-Barrera et al., 2020). This limitation is particularly important in the analysis of expressive language abilities of young children with ASD who are more susceptible to stereotypic speech, which could inflate the LENA measures. Future research should consider including an additional qualitative analysis of the language spoken by children recorded by the LENA technology.

Conclusions

The present study expands on the results of Bak et al (2019) and Trembath et al (2019) who analyzed the expressive language trajectories of minimally verbal children with ASD by analyzing the expressive language trajectories of minimally verbal preschool aged children receiving intensive instruction during a year of comprehensive EIBI. The results demonstrate a waxing and waning of child language growth over the course of a year, consistent with prior literature (Bak et al., 2019; Trembath et al., 2019). The authors documented statistically significant changes in child language trajectories for the sample of children on CV and TC LENA measures across the school year. Though the individual child language trajectories are highly variable, the increases in trajectories at the group level were significant for CV and TC over the course of the year.

Overall, the present investigation demonstrates that many minimally verbal pre-school aged children with ASD exhibit growth in expressive language trajectory in EIBI. Child-level analyses can be valuable to researchers in future investigations of expressive language trajectories to better understand the subtleties in the results of the group-level analyses.

Additionally, though all subgroups demonstrated significant change across a school year, results show EIBI had an equal benefit, in terms of expressive language growth, for children of all expressive language levels. These results highlight the importance of repeated measures of child expressive language because of the variability that can observed within an individual over time, especially minimally verbal children with ASD for who it can be more challenging to accurately capture the expressive language ability.

CHAPTER FOUR: LANGUAGE ENVIRONMENTAL ANALYSIS TECHNOLOGY AND APPLIED BEHAVIOR ANALYSIS: A TUTORIAL

Early language exposure is an important social determinant of health that impacts expressive language development across a child's lifespan (Irwin et al., 2007; LoRe et al., 2018). The World Health Organization and the American Academy of Pediatrics specifically recognize a child's social environment as a critical element in the formation of neural connections essential for the child's long-term physical and social well-being (American Academy of Pediatrics, 2014; Irwin et al., 2007). Additionally, studies across early childhood disciplines, such as applied behavior analysis, speech-language pathology, child development, communication sciences, and special education (e.g., Bak et al., 2019; Beecher & VanPay, 2021; Hart & Risley, 1995; Rogers et al., 2015; Snow, 2021) emphasize the importance of the early language environment on child expressive language developmental trajectories.

Hart and Risley (1992, 1995) conducted a seminal study evaluating child language environments that ignited empirical interest regarding the impact of a child's home language environment on child development. Specifically, Hart and Risley video-recorded "everything" in the child's home environment for one hour every month for 2.5 years and transcribed all vocalizations emitted by the adults and the child. This groundbreaking study was the first to observe early childhood experiences in children's homes and explored how those experiences impact education and development prior to a child entering a classroom. The purpose of the present tutorial is to provide practicing behavior analysts with information about recently developed technology that can help facilitate recommendations from Hart and Risley about improving language development for all children by intervening at the language environment level (e.g., parents, educators).

Impact of Language Environment on Language Development

Hart and Risley (1992) demonstrated that, on average, children of high SES families experienced more language before entering preschool than their lower SES peers. Hart and Risley estimated the difference in language exposure was 30 million words, known as the 30-million-word gap. Additionally, the children who experienced the benefit of 30 million words had more extensive vocabularies and steeper language developmental trajectories that were associated with better educational outcomes evident when the children were in the third grade (Hart & Risley, 2003). This is encouraging because irrespective of SES, adults can modify their behavior to support child development (Brito et al., 2020; Zhang et al 2015). The therapeutic effects of greater rates of expressive language exposure underscores the importance of providing language-rich environments to all children, especially children who could be at risk of low language exposure in early childhood.

Although the quantity of expressive language in a child's environment represents only one type of measure (e.g., quality indicators of language interactions are also vital to a child's language development), research has shown that increasing the quantity of parent expressive language is correlated with an increase in qualitative measures of parent-child interaction that promote child language development (Hart & Risley, 1995). Specifically, Hart and Risley found that all families in their study used "business" language around their children to correct child behavior (e.g., "no, don't do that") and give instructions (e.g., "put your shoes on"). However, the families who exhibited greater quantities of expressive language also used greater quantities of "non-business" language that was positive or affirming, was more responsive to their child's experiences and provided the child with language learning opportunities (e.g., "that is the sky, the sky is blue!"). Furthermore, when the researchers instructed families who had low quantities of expressive language to increase expressive language around their children, the increase was automatically associated with an increase in “non-business” language. This result is important because it suggests that interventions focused on increasing the quantity of expressive language may result in increases in the use of more positive and responsive language observed in homes (Hart & Risley, 1995).

Despite the benefits of using naturalistic repeated measures to capture the quantity of expressive language children experience in their home environments, there are practical limitations to quantifying language environments. This includes, until recently, labor intensive demands to continuously record and transcribe audio (Crowley-Koch & Van Houten, 2013). Directly recording data in home environments would require personnel who have the expertise to record reliable data to frequently visit family homes for long durations which can be costly and time-consuming (Crowley-Koch & Van Houten, 2013). In their book, Hart and Risley discuss scheduling home visits to be one of the most time-consuming aspects of recording home environmental data. To quote Hart and Risley, “[n]one of us [researchers] took a day of vacation for more than three years… [the caregivers’] schedules completely determined ours” (1995, p 41). Additionally, the process of transcribing the audio data for analysis was also labor-intensive. Hart and Risley (1995) describe transcription taking six hours for every hour of audio data with an additional hour for every extra person present in addition to a caregiver and the child in the home environment. As a result of these labor-intensive demands, a more practical way to record and analyze the language that children experience is necessary for clinical use.

LENA Technology

Building upon Hart and Risley’s (1992) longitudinal study, a team of researchers, educators, and engineers collaborated to form LENA, with the mission to support researchers investigating language acquisition to measure child expressive language experiences more efficiently (see https://www.lena.org/). Technology developed by LENA includes the LENA Digital Language Processor (DLP), an automated measurement tool created for clinicians and researchers to measure adult and child expressive language interactions in the child's natural environment (Ford et al., 2008). The LENA DLP is a small (8.56 x 5.56 x 1.27 cm), 56g device that can record audio in a child's environment for up to 16 hrs (Ford et al., 2008). A clinician or researcher places the LENA DLP inside the chest pocket of specially constructed clothing with snaps to keep the LENA DLP in place. When a clinician or researcher connects the LENA DLP to a computer with the LENA software, the software disaggregates the expressive language data for features such as amplitude and intensity of the audio recording to differentiate between types of sounds such as voices, noise, or electronic sounds (Xu et al., 2008). The clinician or researcher can then download the daylong audio reports as excel files for analysis in prespecified increments ranging from 5 minutes to day-long durations. The automated reports include graphic displays of measures that clinicians can download for further analysis (Xu et al., 2008).

Independent researchers have validated LENA to evaluate expressive language in many different environments and with children who have various expressive language disorders (Ganek & Eriks-Brophy, 2018). The variety of variables the LENA system can capture contributes to a global understanding of the audio environment a LENA wearer experiences and lends sensitivity to environmental changes that practitioners, researchers, and parents can quickly analyze (Greenwood et al., 2018; Suskind et al., 2013). As a result, LENA technology has gained recognition as a tool for language acquisition research and researchers have emphasized that LENA technology has exciting potential for application in clinical practice (Ganek & Eriks-Brophy, 2018; Wang et al., 2017).

LENA Technology to Support Behavior Change

Researchers have shown that practitioners can use LENA technology to support behavioral interventions by delivering quantitative linguistic feedback to caregivers to improve a child's language environment at home (Suskind et al., 2013, 2016; Gilkerson et al., 2017). The interventions used by researchers use procedures common to staff or parent training programs in the ABA literature with modeling, practice, feedback, goal setting, and scaffolding (Straiton et al., 2021; Wyatt Kaminsi et al., 2008) For example, Suskind et al. (2013) used LENA technology to provide weekly feedback to caregivers of typically developing toddlers after receiving a single-parent training session to enrich their child's home language environment. The intervention was simple and consisted of goal setting with performance feedback. Specifically, Suskind et al. (2013) collected baseline data on the number of adult words children experienced in their home. Researchers then provided a 1-hr language-focused educational intervention to the caregivers. During the educational intervention, the interventionist provided the caregiver with information on child language development and information on LENA technology. The interventionist then reviewed baseline data with the caregiver, ensuring the caregivers accurately interpreted information derived from LENA. Finally, researchers provided caregivers with tips to increase the quantity of language and how to engage in more TC with their child to enrich the child's language environment. After this single educational intervention session, caregivers used LENA technology to collect weekly recordings for 6 weeks and the interventionist provided the caregivers with LENA feedback between each recording session. Suskind and colleagues report that beyond providing the LENA feedback and initial educational intervention, there were no explicit discussions of goal setting by the interventionist with the caregiver. The results demonstrated that caregiver AWC and TC between child and caregiver significantly increased after the educational intervention session and quantitative linguistic feedback.

In 2016 Suskind et al. extended their 2013 study by including explicit discussions of goal setting between the caregiver and interventionist. In addition, they included a follow-up phase to measure the effects of the intervention after 3 months. Goal setting consisted of the caregiver reviewing the prior week's LENA Feedback Report that included total daily measures of AWC and TC. The interventionist presented the data in hourly increments. Caregivers received this data with information of how their data compared to a national average collected from the LENA Natural Language Study (LENA, 2008) and data from the previous recording. Weekly goals were set for AWC and TC. Results indicated that the caregiver-directed intervention significantly increased caregiver language and TC at home. Follow-up analyses demonstrated that effects may slightly diminish as time goes on. Specifically, caregiver AWC diminished by 186 words per hour and by 11 TC per hour after 3 months follow-up from treatment. However, AWC remained higher in follow-up than during baseline.

Gilkerson and colleagues (2017) extended the work of Suskind et al., (2016) and documented the long-term benefits of an online caregiver-directed intervention to elevate the quantity of expressive language in the child's language environment. The online intervention consisted of six 10 min webinars that encouraged caregivers and provided information on language-related topics including tips to increase TC. During the online intervention, caregivers had access to a parent discussion forum to engage with other caregivers, had access to video examples of how to implement each tip, and written materials to implement language environment enrichment strategies. Phone coaching was also available to caregivers and consisted of discussions of language enrichment strategies and offered the caregivers an opportunity to ask questions. The practitioners required caregivers to hold one phone coaching session after the first recording and encouraged caregivers to hold three phone coaching sessions per month but could use the service as needed. Gilkerson et al. found that caregiver AWC and TC increased and maintained post-intervention and was most beneficial for households that began with below-average language use, as measured by LENA technology. Moreover, unique to their study, Gilkerson et al. documented improvement in child-specific language outcomes over time associated with caregiver participation in the intervention.

Gilkerson and colleagues (2017) found benefits of a 3-month online caregiver-directed intervention with effects that persisted nine months after completion. Part of that long-term benefit may be because of how the practitioners scaffolded feedback and faded over time instead of abruptly removing the feedback. Caregivers first received intense feedback from LENA recordings during the three-month intervention and incrementally less feedback from LENA recordings over the next nine months. Specifically, caregivers received 10 feedback sessions using LENA data during the first three months, then received feedback biweekly for three months post intervention, and finally monthly for 6 additional months post intervention.

These studies illustrate a promising use of LENA technology for feedback purposes with at-risk clients of low language exposure (i.e., low SES, children with language delays, hard of hearing children, and families with low language use in their home) and subsequently associated diminished developmental outcomes. As a feedback component to intervention focused on increasing language exposure, LENA technology is directly relevant to behavior analysts interested in increasing the quantity of adult language in client homes, clinics, and schools. Additionally, behavior analysts could implement brief interventions with data collection using

LENA technology, such as those described by Suskind et al. (2013; 2016) in early intervention programs for children with ASD.

LENA technology's ability to efficiently measure and analyze day-long natural environment language samples, offers an in-depth understanding of child language ability that can inform intervention in addition to language assessment (Bak et al., 2019; Bak et al., 2021; Burgess et al., 2013; Trembath et al., 2019). Nevertheless, ABA research has underutilized automated data collection devices in research (Bak et al., 2021; Crowley-Koch & Van Houten 2013). Therefore, behavior analytic practitioners may not be familiar with automated data collection devices, such as LENA technology, and how to use the technology to increase the amount and variety of data collected on human behavior (Bak et al., 2021).

The present paper is for behavior analytic practitioners working with young children to learn how to use LENA technology as part of behavior analytic services to encourage practical use of LENA technology. The authors will discuss considerations for using LENA technology with clients, students, or similar. Information will include which LENA programs are available for behavior analytic use with young children, how practitioners can use LENA technology in behavior analytic services, and considerations for practical use of LENA in behavior analytic services. Finally, examples provided throughout the paper will illustrate the use of LENA technology in behavior analytic practice to improve the language environments of young children.

Description of LENA Programs Behavior Analysts Can Use

LENA's mission is for practitioners and researchers to use the technology to improve child outcomes through the measurement and intervention of child language environments (see https://www.lena.org/history/). LENA offers several programs for clinicians to use LENA technology to support the language development of children in different environments. See Table 1 for descriptions of the four LENA Programs. Specifically, LENA Grow may be the most helpful to clinicians in clinical, classroom, or home settings to improve the language environments and support child language development. As of 2021, LENA reports serving over 1,300 classrooms and over 11,000 children across 27 states in the United States of America with LENA Grow (LENA, 2021). LENA offers professional development and certification for teachers interested in using LENA Grow that consists of goal setting and coaching to implement LENA talking tips (see https://www.lena.org/teacher-certification/). Of children who started the program with below average interactions with teachers, children experienced an increase of 52% in conversational interactions. Notably, children who experienced the lowest amount of language initially benefited the most from the program (LENA, 2021). Finally, teachers who used LENA Grow report increased enjoyment and confidence in their teaching (LENA, 2021).

Additionally, clinicians can use LENA Home, another LENA program, to complement current caregiver coaching practices. As part of comprehensive early intervention, clinicians can use LENA HOME to improve caregiver and child interactions using a strengths-based approach to foster child language development. Researchers designed LENA Home for clinicians to integrate it within existing programs. Some programs that have implemented LENA Home include Head Start and home visiting care programs. Currently, researchers are conducting a randomized control trial to assess the feasibility and efficacy of LENA Home as part of Every Child succeeds home visiting curriculum (Every Child Succeeds, n.d.).

Table 1

Descriptions of LENA Programs

LENA Program	Year	Who Uses LENA	Purpose	Website Address
LENA SP and LENA Pro	2004	Nonprofits, hearing and speech schools, Early Intervention Programs, language acquisition researchers	Reliable, secure, and detailed language environment data	https://www.lena.org/lena-sp/
LENA Start	2015	School districts, libraries, healthcare systems, and community-based non-profits	To reinforce caregiver-child interactions and support school readiness	https://www.lena.org/lena-start/
LENA Grow	2016	Home- and center-based care settings with infant, toddler, and preschool educators and family childcare providers	Provide professional development to improve educator-child interactions and support child school readiness	https://www.lena.org/lena-grow/
LENA Home	2018	School districts, Head Start organizations, and home visiting programs	Increase collaboration between home visitors and families to improve quality of child language environment	https://www.lena.org/lena-home/

Note. The authors combined LENA SP and LENA Pro because of the overlap in purpose of the versions.

Data Collection with LENA Technology. The frequency of data collection depends on the purpose of the data collection, but if behavior analysts use LENA technology to monitor change in the environment associated with intervention, more frequent data collection may be necessary. For example, Kisshida and Kemp (2020) used LENA technology to measure TC between caregivers and their child in relation to a graphical feedback intervention, and the practitioners collected LENA data weekly to provide feedback in a timely manner. This differs from Bak et al., (2019) who collected LENA data monthly to assess language acquisition of children in an educational setting overtime.

Types of LENA Data for Behavior Analytic Clinical Purposes. LENA technology is also capable of measuring several variables relevant to behavior analytic practice. Together, the many measures captured simultaneously offer behavior analytic practitioners a global understanding of a child's language environment that practitioners could use to inform and individualize intervention in countless ways. The authors will discuss three of the most used measures (i.e., AWC, TC, and CV).

As previously discussed, a team of team of researchers, educators, and engineers developed LENA technology in response to Hart & Risley's seminal study that evaluated the relationship between the language expressed by adult caregivers and child developmental and academic outcomes. Accordingly, the most often reported LENA measure in literature evaluating child outcomes in relation to their environment is AWC (See Chapter 2). Adult word count quantifies the number of words spoken by adults within a 6-foot distance of the child (Xu et al., 2008). In addition to the number of adult words, LENA can quantify adult female words, male words, and the number of adult male or female words spoken near the focal child versus far from the focal child.

Consistent with the results of Hart and Risley (1995), several studies have used LENA technology to evaluate child outcomes in relation to the quantity of adult language exposure and have found that greater quantities of adult language are associated with more favorable child development (Dwyer et al., 2019; Greenwood et al., 2020; Swanson et al 2018). These results are encouraging because adults can modify their vocal verbal behavior to support child development. Behavior analytic practitioners could use LENA to obtain frequent measures of adult language in environments where children demonstrate language delays (e.g., early intervention for children with ASD). Practitioners could then use a behavioral intervention, such as the goal setting and performance feedback procedures described above (e.g., Gilkerson et al., 2017; Suskind et al., 2013), to mediate adult behavior change leading to improved outcomes for children.

A second LENA variable, TC count, measures the number of interactions between adults and the focal child wearing the LENA DLP (Xu, et al, 2008). Conversational turn count is another variable that has demonstrated importance to child language development including increased connectivity in white matter, activation of the language-center of the brain, improved reading abilities, higher IQ scores, increased social-emotional regulation, and better reasoning abilities (Gilkerson et al., 2018; Gomez & Strasser, 2020; Merz et al., 2020; Romeo et al., 2018; Romeo et al., 2018; Romeo et al, 2021;Sundquivist et al., 2021; Zimmerman et al., 2009 study 1). Romeo et al. (2018; 2021) advises early intervention programs to coach parents to talk *with* their children and exchange conversation to promote neural development and language acquisition. Similarly, Sundquivist et al. (2021) and Zimmerman et al. (2009) emphasize the need to teach parents not only the value of quantity of speech, but also to engage in intentional conversation with children as much as possible, even during activities commonly identified to promote language acquisition, such as during book-reading. As many practicing behavior analysts have an interest in social interactions of their clients, they could use LENA to efficiently collect data over an extended period (e.g., entire day) where social environments are frequently changing.

Another common LENA measure is CV. Child vocalization count is a measure of a child's vocal expressive language measured by a consonant and vowel separated by 300 milliseconds and does not include vegetative sounds such as crying or blowing raspberries (Xu et al., 2008). Measuring CV, in relation to other LENA measures such as TC and AWC, may be useful to behavior analysts to help determine when to introduce AAC devices (Bak et al., 2019;

Thieman et al., 2014). Specifically, Thieman et al. (2014) recommends that if parent or adult language remain high and stable, but child vocal behaviors remain low, AAC devices may be appropriate at as early as two years old, so children do not miss the critical early language learning opportunities prior to age three years.

Environmental Context of LENA Data. When collecting LENA data, it is important to understand the context of the environment that the behavior analyst collected the LENA data. In studies that use LENA technology to measure the language environment in applied contexts, researchers often obtain baseline levels of LENA measures. In a clinical or educational setting, a behavior analyst may encourage registered behavior technicians (RBT) or caregivers to log child activities for the duration of LENA recordings that behavior analysts can use to examine the impact of environmental stimuli on LENA measures. For example, it may be beneficial for an early intervention provider to know if a child engaged in higher vocalizations during specific play activities, such as when on a playground.

By logging information about the environment throughout the day, clinicians can identify activities associated with higher quality language environments. For example, in a study by Clemens et al. (2021), the researchers compared language measures across daily activities associated with language acquisition (e.g., reading, singing, playing) to see how CV and TC between caregivers and children differed. The researchers found that book reading occasioned higher levels of language than other activities. Identifying activities that caregivers are already doing with their children that occasion elevated quantities of language could help to individualize services from a strength-based approach. In an educational setting, practitioners could use LENA technology to provide an objective measure of inclusivity of students with disabilities in the general early education or care environments. To measure inclusivity, practitioners could assess the amount of language children with disabilities experienced as compared to their typically developing peers in the same environment.

In addition to identifying activities when a child experiences high rates of language that foster language acquisition, it is also important to identify activities that are associated with lower rates of language. Sundquivist and colleagues (2021) found that some activities (i.e., TV watching, parent media device use during childcare routines) were associated with lower rates of TC. This yields valuable information because there may be opportunities for clinicians to work with caregivers to change activities or insert themselves into historically independent activities to improve a child's language environment and promote language acquisition.

LENA DLP Use with Children. Recent studies have begun to describe how clinicians and clients regard the use of LENA technology in the clinical environment. Overall, clinicians and clients have reported LENA technology to be easy to use and may help to foster clinician-client collaboration. Charlton and colleagues (2014) identify the utility of LENA technology in both clinical and classroom settings for its ability to monitor language development throughout therapy and to show behavior change in the classroom. Weil and Middleton (2010) shared these ideas in an evaluation of parent intervention programs provided by clinicians. Specifically, Weil and Middleton (2010) reported that SLPs found LENA technology easy to use with clients, easy to interpret the results of LENA analyses, and found that LENA reports were well-received by caregivers. Charlton and colleagues (2014) also found that children with social emotional behavioral difficulties (SEBD) wore the LENA DLP without any obstacles and that the characteristic behaviors of children with SEBD did not affect the LENA measures.

Increasingly, clinical researchers are recognizing LENA technology for its family-centered approach to promote child development and for its utility to provide ecologically valid measures of language children experience. Romeo and colleagues (2021) identify the necessity of programs to support caregivers in fostering a high-quality language environment for their children. The use of LENA technology in such programs could help to individualize services, help to foster home-school collaboration, and provide more comprehensive services. Addressing the child's environment and the cumulative effects of adult behaviors that promote child development with RBTs and caregivers may not just change behaviors in the short-term but could help to change the culture around daily activities, such as engaging in shared book reading and intentional conversation, to support long-term child development (Beecher et al., 2021). Considering a child's environment also highlights the importance of including people integral to the child's life, such as all immediate caregivers and extended family members, to help sustain behavior change to support child development (e.g., increased rates of TC, AWC; Hoffman et al., 2020, Johnson et al., 2014; Shapiro, 2021 VanDam et al., 2012). Beecher and colleagues (2021) describe caregiver excitement to share LENA reports that summarize a child's home language environment with other caregivers and friends. This excitement speaks to the social validity of the use of LENA technology with clients, but also demonstrates how LENA can foster a community to support child development.

LENA Technology as Part of Behavior Analytic Services

Behavior analysts may use LENA technology in ABA services in several ways including to inform level of support, as a behavior change agent, to monitor progress, aid in data-based decision making, and to support multi-disciplinary team collaboration. Readers should note that the authors provide several examples from the perspective of a clinician collaborating with a caregiver, but behavior analysts could apply the uses of LENA to data-based instruction in clinical or school settings. In these examples, instead of reviewing data with caregivers of the focal child, the behavior analyst may review the LENA data with clinical staff (i.e., RBTs) and educators.

Inform Level of Support. Behavior analysts may use LENA technology to assess baseline levels of language exhibited by either children or adults in home or clinical settings. Practitioners may use LENA data to inform the intensity or type of support provided by clinicians throughout treatment. Gilkerson and colleagues (2017) proposed that practitioners may use LENA technology as part of a multi-tiered system of support framework to individualize and intensify (e.g., one-to-one and home visiting vs group coaching) the level of caregiver support. Upon enrollment to a clinic, for example, a practitioner could send a LENA DLP home with a family to assess baseline levels of child vocalizations and adult language the child experiences over the course of a day. Homes with low rates of child language exposure may benefit from more family training sessions and increasing language exposure. Gilkerson et al (2017) state that families with lower baseline levels will be those that are more responsive to caregiver intervention or coaching. LENA conducted the Natural Language Study that generated the first edition of percentile norms of child's vocalizations and the AWC and TC that family exposes a child to. Using these norms, behavior analytic clinicians can individualize the level of support to provide a family upon enrollment of services.

Tool to support Behavior Change. The efficiency of acquiring language data using LENA technology gives behavior analysts the opportunity to create individual goals and provide feedback to caregivers throughout caregiver coaching. Suskind et al. (2013) describes how a clinician may review the LENA data with a caregiver. Specifically, clinician and caregiver should discuss the caregiver's role in the language environment, discuss opportunities unique to the family to enhance the child's language environment, and graph the language data together so the behavior analyst and caregiver can monitor progress. To guide the discussion of what opportunities a caregiver may have to enhance the language environment, LENA® has downloadable Talking Tips (see https://info.lena.org/14-talking-tips) that outline 14 research-based techniques for increasing early talk with young children, that a behavior analyst may present as starter material to the caregiver. Applied behavior analysts may use their expertise (e.g., Behavioral Skills Training; Miltenberger, 2004) to teach caregivers specific skills to engage with their child and increase language exposure.

Progress Monitor. Behavior analysts could also use LENA technology as a tool to monitor progress through the continual evaluation of a behavior-change intervention. Behavior analysts could monitor child language acquisition over time and monitor environmental language data in relation to intervention (Greenwood et al., 2020). For example, if a behavior analyst collects LENA data monthly, they can graph CV to show a child's expressive language acquisition trajectory. Bak et al. (2019) and Trembath et al. (2019) are behavior analytic researchers who graphed child expressive language acquisition trajectories over the course of an academic year in both school and clinical settings, respectively. Over time, the behavior analyst may use the graphed LENA data to make data-based decisions to guide intervention.

Child expressive language trajectories developed using child vocalizations as measured by LENA technology may inform intervention type and intensity. For example, if a child is not demonstrating adequate expressive language acquisition, then intensifying expressive language intervention may be necessary or a clinician may decide to supplement instruction with an AAC device to provide the child with another avenue of expressive language. Recently, Bak et al. (2019) and Trembath et al. (2019) emphasized the value that LENA technology could lend to detecting minute changes across a variety of variables in therapeutic environments. Bak et al.

observed the language trajectories of both minimally verbal and verbal children with autism in an elementary special education classroom over the course of a school year. Bak et al. found CV and TC increased over the course of the school year for verbal children with ASD but fluctuated and remained low for children who were minimally verbal children with ASD. Bak et al. (2019) suggested that consistent low rates of child vocalization counts collected using LENA could prompt educators to provide instruction on AAC to those children because children who exhibit consistent low levels of vocalizations and TC may have difficulty acquiring vocal verbal language. In these cases, LENA technology could help behavior analytic practitioners determine for who and when to begin more intensive AAC instruction.

Multi-disciplinary Team Collaboration. Language acquisition researchers have advocated for the use of LENA technology by clinicians, educators, and SLPs who all may work in collaboration with behavior analysts to provide services and support the development of young children. Ganek and Eriks-Brophy recently conducted a literature review to promote the use of LENA with SLPs and discussed how SLPs could incorporate LENA technology into practice. The behavior analyst could make the LENA data available to all the collaborating professionals as a meaningful measure of child experience and language acquisition. LENA technology could help practitioners across disciplines collaborate by providing objective behavioral data that the professions can access to inform patient-centered services from a strengths-based perspective. The LENA measures are equally valuable to collaborating providers because they are automated objective measures that the professions would collect and interpret the same way across disciplines. The automated objective measure that LENA technology offers could be a valuable aspect to help improve collaboration between practitioners such as behavior analysts, early childhood educators, SLPs, and audiologists.

Considerations for Practical Use of LENA in Behavior Analytic Services

Given the discussed benefits of using LENA technology as part of behavior analytic practice, the authors offer some additional considerations for troubleshooting obstacles that behavior analysts may encounter when using LENA technology as part of behavior analytic services. The first consideration that the authors will discuss is the interpretation of TC, especially when working with children with speech disorders. A second consideration is using the LENA DLP with the focal child. Finally, the authors will discuss the protection of client privacy when using LENA technology as part of behavior analytic services.

Conversational Turn Counts. Given the heterogeneous language abilities of children with language delays, researchers and clinicians should exercise caution when interpreting TC when working with children with language acquisition disorders, such as ASD. Researchers, educators, and engineers designed LENA technology to measure the vocalizations of typically developing children between the ages of 2 to 48 months. Children with language acquisition disorders, such as ASD, may display stereotypic or repetitive vocalizations that may overestimate TC, especially in environments with high adult-to-child ratios (Bak et al., 2019). Alternatively, a practitioner may underestimate TC because the measure may not accurately depict how children interact with a conversational partner (i.e., within 5 seconds of an adult's initiation; Bak et al., 2021). To mitigate the over- or under-estimation of TC, practitioners may consider using an average measure derived from consecutive repeated LENA measures.

Child Wearing the LENA DLP. Overall, parents report high social validity associated with using the LENA DLP with their child. However, children may protest wearing the LENA DLP, as demonstrated through a range of behaviors that researchers have discussed in published studies (e.g., crying, grabbing the LENA DLP, refusing to put on the LENA t-shirt; Bak et al., 2019). A behavior analyst’s expertise in reinforcement, stimulus-stimulus pairing, and shaping can be helpful with using the LENA DLP with clients. For example, the clinician can pair, or deliver a reinforcer concurrent with the LENA DLP. During this pairing procedure, the LENA DLP, a previously neutral stimulus, becomes associated with the properties of the reinforcing stimulus (Skinner 1938). Additionally, a behavior analysts may use shaping, or systematically reinforcing successive approximations toward a skill, to help teach the child to put on the LENA shirt, or to allow the caregiver or clinician to dress the child in the LENA shirt, if the child has difficulty dressing (Koegel et al., 1978). A behavior analyst can use both stimulus-stimulus pairing and shaping in preparation to record language environment audio using the LENA DLP with clients.

LENA Recording Interruptions. Researchers designed LENA technology to measure daylong durations of a child’s language environment, up to 16 hours (Xu et al., 2008). For shorter durations of recordings, researchers recommend recording at least 1 hour of language data, with longer recordings yielding more reliable data (Xu et al., 2008). In applied settings, such as clinic and home environments, it may not be possible for the child to continuously wear the recorder such as during sleeping, bathing, or other water activities (e.g., Charron et al., 2017; Elmquist et al., 2020; Gilkerson et al., 2017; Irvin et al., 2017; Thiemann-Bourque et al., 2014; Tulviste & Tamm, 2021; Wang et al., 2021). In many of these applied studies when the interventionist or caregiver took off the recorder, the researchers recommended placing the recorder near (i.e., within six feet) the child to capture as much language and interaction during these times as possible and to put the shirt back on as soon as possible.

Protect Client Privacy. Many behavior analysts are providing medical or educational services, and the protection of privacy is of utmost importance. LENA protects client privacy through multiple privacy protections (see https://www.lena.org/data-privacy/ and https://www.lena.org/privacy-policy/ for specific privacy information about LENA's secure cloud-based database). It is important to note that LENA Start, LENA Grow, and LENA Home do not store any recorded audio and the only product from the environmental recordings is the quantitative reports on the environmental variables such as the number of adult words, CV, and TC. However, LENA SP, primarily used by language acquisition researchers, is the only LENA Program that retains audio in addition to producing automated reports of the child's language environment and there are privacy measures in place to protect clients. In addition to the privacy protections in place by LENA, clinicians may consider using client identifying numbers in lieu of using client names when creating a client profile for LENA to further protect client privacy.

Conclusion

Written for behavior analytic practitioners, the present paper introduces how clinicians can incorporate the use of LENA technology in behavior analytic practice to improve the language environment of young children with or without disabilities. Incorporating LENA technology in behavior analytic practice would address concerns raised by Bak et al. (2019) regarding the use of automated data collection procedures in ABA research and practice. With this information, behavior analysts should consider using LENA technology in addition to standardized language assessments to better understand child language ability and exposure to inform intervention. Specifically, upon enrollment of services, behavior analysts may collect daylong LENA recordings to obtain a baseline of child expressive language abilities, inform parent coaching intensity, and inform behavior analytic programming focused on vocal verbal behavior. Behavior analysts may consider using LENA technology to track language acquisition trajectories of child clients. Child expressive language trajectories may inform intervention decisions such as when to introduce AAC. Additionally, repeated LENA measures in home environments can be part of comprehensive parent coaching services to provide feedback to caregivers about the role they play in their child's development. Feedback from LENA reports may foster caregiver-clinician collaboration and help the clinician to provide individualized and strengths-based services to each family. Additionally, behavior analysts can use LENA technology to foster collaboration between practitioners working together to provide cohesive services to a family by providing an automated objective measure of child expressive language acquisition. LENA technology gives Board Certified Behavior Analysts a unique opportunity to address issues originally identified by Hart and Risley (1995).

CHAPTER FIVE: DISCUSSION

Early language exposure sets the foundation for literacy development associated with enhanced life outcomes, including language acquisition and academic achievement (Beecher & Van Pay, 2021; Demir-Lira et al., 2021; Hoff, 2006; Suskind, 2015). The first three years of a child's life is a critical period of development and children benefit from listening and engaging with caretakers to form early neural connections essential for language development (Gilkerson et al., 2018; Gomez & Strasser, 2020; Irwin et al., 2007; LoRe et al., 2018; Merz et al., 2020; Romeo et al., 2018; Romeo et al., 2018; Romeo et al, 2021; Sundquivist et al., 2021). A team of researchers, educators, and engineers developed LENA technology to ease the data collection procedures necessary to frequently assess day-long natural language samples pioneered Hart and Risley (1992; 1995).

Many language acquisition researchers have used LENA technology to take single recordings to assess a child's language environment (See Chapter 2). However, researchers are increasingly using LENA technology to take repeated measures of individual's language environments, especially in home environments (See Chapter 2). The present dissertation adds to the literature that uses LENA technology to take naturalistic repeated measures in educational settings and makes suggestions for clinical research (See Chapter 3) and practice (see Chapter 4). The results of the present dissertation yield three interconnected themes, which the primary author will discuss throughout the remainder of this chapter. The three themes include 1) the use of LENA technology to collect naturalistic repeated measures of a child's language environment, 2) the use of LENA technology to inform data-based decision making, and 3) the use of LENA in educational settings by educators.

Naturalistic Repeated Measures

Chapter 2 provided evidence that suggests most language acquisition researchers who use LENA technology do not measure the language environment with frequent repeated measures. Language acquisition researchers who have used repeated measures with LENA technology, including Chapter 3, have discussed the need to evaluate child expressive language development, especially among individuals with language delays or disorders. For example, Chapter 3 of the present dissertation approached the opportunity to use LENA technology as a naturalistic repeated measure by assessing the expressive language trajectories of minimally verbal children during one year of EIBI. The study in Chapter 3 is a valuable contribution to existing literature because the evaluation used day-long naturalistic repeated measures obtained in a clinical setting with minimally verbal children with ASD. This study is different from prior studies conducted by language acquisition researchers because prior studies evaluating language trajectories of minimally verbal children with ASD were not preschool-aged children in a clinical setting receiving quality intervention (i.e., Bak et al., 2019) or had not collected day-long recordings (i.e., Trembath et al., 2019).

Since 2004, language acquisition researchers have had access to LENA technology that eases the frequent collection of naturalistic language measures and have published data that practitioners can use to inform practice. However, there is a dearth of research that evaluates the use of LENA technology to capture the expressive language trajectories of children through naturalistic repeated measures to inform clinical intervention. There are many published studies using naturalistic repeated measures as a tool for behavior change during a caregiver-mediated intervention (e.g., Suskind et al., 2013, 2016), but not as a measure to continually assess comprehensive early intervention services and inform intensity and type of communication (e.g., vocal verbal versus AAC; Bak et al., 2019). Such research may demonstrate that language acquisition researchers could predict which children would benefit from a specific intervention. Prior research has established that expressive language development is associated with more-favorable life outcomes (Dwyer et al., 2019; Greenwood et al., 2020; Swanson et al 2018). The clinical benefit from such research may result in the ability to provide children with the opportunity to contact instruction more tailored for individual clients.

No matter how practitioners use LENA technology; they need to be science practitioners to carefully interpret and use LENA data. Specifically, practitioners in clinical settings may consider using LENA technology to collect naturalistic repeated measures of child expressive language, in addition to using standardized language assessment. Specifically, practitioners could use naturalistic repeated measures in behavior analytic practice to inform clinical staff and caregivers about a child's language environment over time (Chapter 4).

Data-based Decision-making

The frequent collection of naturalistic repeated measures may lead to another form of data-based decision-making (DBDM) within clinical settings. A commonly accepted definition of DBDM is the systematic collection and analysis of different kinds of data to inform educational decisions (Mandinach & Schildkamp, 2021 as cited in Hamilton et al., 2009). Since the No Child Left Behind Act in 2001, federal, state, and local education policymakers have increasingly emphasized DBDM to drive the evidence-base of education and advance student achievement (Hamilton et al., 2009; Mandinach & Schildkamp, 2021; Wang et al., 2017). As educators adopt data collection methods, it is important that educators collect information based on the needs of students in every-day practice and that educators are using a variety of assessments to inform practice (Mandinach & Schildkamp, 2021; Will et al., 2019). Language acquisition researchers have demonstrated that LENA technology can collect naturalistic observational data that practitioners can use as feedback under intervention conditions (e.g., Suskind et al., 2013; 2016).

Specifically, many language acquisition researchers have demonstrated that practitioners can use LENA technology as a tool to provide environmental feedback (See Chapter 2). When implemented with goal setting, modeling, and practice of intervention procedures, practitioners can use LENA data to inform caregiver-mediated intervention (See Chapter 4). In addition to data-based decisions in terms of caregiver-mediated intervention, researchers have proposed that data collected by LENA technology can inform within-clinic intervention decisions (See Chapter 3). Bak et al. (2019) and Trembath et al. (2019) suggest the assessment of child expressive language trajectories can inform for who and when to transition minimally verbal children with ASD from vocal verbal expressive language to AAC device instruction. Deciding when to transition children to AAC instruction is critical if children are not making progress in vocal verbal language development to allow the child opportunity to learn how to communicate via alternative forms.

Currently, there is evidence that indicates LENA technology might be useful to practitioners to inform clinical data-based decision-making (See Chapter 3). However, researchers should conduct more with the specific goal of informing clinical practice to see how feasible it is for clinicians to use LENA technology in clinical practice (See Chapter 4). Individual child expressive language trajectories analyzed in Chapter 3 show most children increased in growth across all three LENA measures during their first year of EIBI. However, for the few children who demonstrated no change or decreased expressive language trajectories, more intensive intervention, and instruction in AAC, may be appropriate (Bak et al., 2019;

Trembath et al., 2019). The results and conclusions drawn from Chapter 3 took place over the course of one year, which reflects the timeframe that clinicians may typically make decisions using standardized assessments. Hypothetically, research evaluating the use of LENA technology to capture expressive language trajectories through naturalistic repeated measures for data-based decision making in clinical practice may be able to someday predict which children would benefit from changes in intervention earlier (e.g., 3 to 4 months). For example, using visual analysis at the individual child data in Appendix D, some children show increasing CV and TC trajectories by months 5 (e.g., for Child 7, 11, 12, 15, 16, 17, 19, 20, 21, 22, 23, and 30), while other children's trajectories remain stable and low or are decreasing by month 5 (e.g., Child 2, 3, 9, 10,13, 14, 23). Other children remain highly variable and difficult to interpret the trajectory by month 5 (e.g., Child 1 and 8). The remaining children did not have enough data points in the first 5 months (i.e., three data points) and a trajectory does not emerge until later in the year (e.g., Child 4, 5, 6, 18, 24, 25, 26, 27, 28, 29, 31).Researchers have proposed to educators, special educators, and speech language pathologists to use LENA technology for purposes of data-based decision making in practice (Chapter 4). Given the lack of research on how to use LENA technology as a tool to inform clinical intervention, practitioners may not want to use LENA technology in this way. However, if practitioners are collecting LENA data to assess the client language environment, it would be important for practitioners to act as a science-practitioner. This is critical if practitioners use LENA data to inform intervention decisions in relation to vocal verbal expressive language instruction.

LENA Technology for Educators

Language acquisition researchers have advocated for clinicians and educators to use LENA technology to increase evidence-base practice in education settings (Wang et al., 2017;

Ganek & Eriks-Brophy, 2018). The automaticity of LENA data recording and synthesis makes it feasible for educators to frequently collect day-long natural language samples to supplement standardized assessment of child expressive language development (see Chapter 4). Though researchers have not extensively evaluated LENA technology in educational settings (see Chapter 2), LENA technology offers great promise as a tool for educators to monitor expressive language environments of children. Educators who use LENA technology report high social validity associated with using the technology (LENA, 2021).

LENA emphasizes the benefits that educators report after incorporating LENA data collection within their classrooms including gained confidence in their teaching, increased motivation, and job satisfaction (LENA, 2021). Other benefits that educators may find when using LENA data to assess child language environments is an increase in collaboration between professionals within a multi-disciplinary team (see Chapter 4). LENA data may provide educators with evidence for the foundation of conversations that advocate for inclusive practices across disciplines to support child expressive language development.

Language acquisition researchers have extensively evaluated LENA technology as a tool to provide feedback to caregivers as part of caregiver-mediated intervention (see Chapter 2). Educators may consider extending those methods and using LENA technology as a tool to provide feedback to school and clinical staff to support child expressive language acquisition. However, there is little research that evaluates the use of LENA technology as a tool to provide feedback to educators in classroom settings. Future researchers should evaluate the use LENA technology as a tool for feedback to educators to support child expressive language acquisition.

Conclusion

Research has demonstrated that child expressive language acquisition is particularly sensitive to the quantity of caregiver language exposure between birth to age three years and affects child achievement throughout their life (Beecher & Van Pay, 2021; Demir-Lira et al., 2021; Hoff, 2006; Suskind, 2015). LENA technology is an automated data collection device that researchers have used to measure child expressive language exposure and development of young children. Language acquisition researchers have proposed that LENA technology has greater application in clinical practice and could be useful to behavior analytic practitioners working with young children with ASD to collect naturalistic language acquisition data to inform intervention services, as suggested by the implications of the present dissertation.

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APPENDIX A: CODEBOOK FOR SYSTEMATIC LITERATURE REVIEW

Section Information	Data extracted/Codes
1. Article Identification	
Author	record extracted data
Year	record extracted data
Journal	record extracted data
2. Participant Characteristics	
Total #	record extracted data
Gender (m)	record extracted data
Age range	record extracted data
Diagnoses	record extracted data
Language	record extracted data
Ethnicity	0= not specified, 1= specified
if specified	record extracted data
Social-economic status	0= not specified, 1= specified
if specified	record extracted data
3. Study Methodology Characteristics	
Design	record extracted data
Independent Variable (IV)	record extracted data
Purpose of the LENA	1 = assessment, 2= feedback
if other	record extracted data
LENA Dependent Variable (DV)	record extracted data
Derived DV?	Yes =1, no = 0
Reliability of LENA	1= present, 0= absent
Validity of LENA	1= present, 0= absent
4. Use of LENA Technology	
Frequency of recordings	record extracted data
Duration of recording	record extracted data
Setting recordings collected within	record extracted data
LENA program used	0= not specified, 1= LENA Grow, 2= LENA Start, 3= LENA Home, 4= LENA SP

APPENDIX B: SUMMARY OF SYSTEMATIC LITERATURE REVIEW INCLUDED STUDIES AND RESULTS

Authors	Year	Number of participants	Participant Age (avg. months)	Participant Diagnoses	Participant Language	Reported Participant Race/Ethnicity	SES	Observational or Experimental	Design	Purpose of LENA	Variables	Derived Variable	Reliability Assessed	Validity Assessed	Number of Recordings per participant	Duration LENA Recording (hr)	Setting	LENA Program
Abney, Warlaumont, Haussman, Ross & Wallot	2014	1	0.25	-	-	-	No	Observational	Case study	Assessment	CV	No	No	No	47	10	Home	-
Adams, Marchman, Loi, Ashland, Fernald, & Feldman.	2018	97	1.30	TD	English, non-English	-	No	Observational	-	Assessment	AWC, CV	No	No	No	1	14.4	Home	-
Ambrose & Vandam	2014	28	1.15	Deaf/HH/HL	English	-	No	Observational	-	Assessment	AWC, CT, TVN	No	No	No	6	12.19	Home	-
Aragon & Yoshinaga-Itano	2012	373	1.58	TD, Deaf/HH/HL	English, Spanish	Hispanic/Latino; White	Yes	Observational	Longitudinal design	Feedback	AWC, CT, CV, SIL, NON, TVN, MAN, FAN, MAF, FAF	No	No	No	1	13	Home	-
Arora, Smolen, Wang, Hartman, Howerton-Fox, & Rufsvold	2020	26	3.97	Deaf/HH/HL	English	-	No	Observational	-	Feedback	AWC, CV, CT, TVN	No	No	No	2	16	Home, Classroom	-
Bak, Plavnick, Byrne	2019	9	8.00	ASD	-	-	No	Observational	Pre-post and longitudinal design	Assessment	CV, CT	No	Yes	No	32	6.66	Classroom	-
Beecher & Van Pay	2020	56	1.45	-	English, non-English	White, Black/African American; Asian/Asian-American/Pacific Islander, Other	Yes	Experimental	Quasi-experimental comparison design	Feedback	AWC, CT, CV, TVN	No	No	No	9	10	Home	-
Beecher & Van Pay Study 1	2021	41	1.29	-	English, Spanish, Chinese, other-not Arabic or Korean	Caucasian/White, African American/Black, Asian/pacific Islander, Native American/Alaka Native, other, preferred not to answer, Hispanic/Latino	Yes	Experimental	Pre-post repeated-measures growth design	Feedback	AWC, CT	No	No	No	8	10	Home	LENA Start
Beecher & Van Pay Study 2	2021	105	1.29	-	English, Spanish, Chinese, Arabic, Korean, other	Caucasian/White, African American/Black, Asian/pacific Islander, Native American/Alaka Native, other, preferred not to answer, Hispanic/Latino	Yes	Experimental	Pre-post longitudinal	Feedback	AWC, CT	No	No	No	13	10	Home	LENA Start
Benitez-Barrera, Angley, & Tharpe	2018	10	4.40	Deaf/HH/HL	English, Spanish	-	No	Experimental	-	Assessment	FAN, MAN	No	No	No	2	7	Home	-
Benitez-Barrera, Grantham, & Hornsby	2020	9	4.04	Deaf/HH/HL	English only, Spanish only, Multilingual: Spanish/ASL/English, Multilingual: English/German, English/ASL	-	No	Observational	-	Assessment	FAN, FAF, MAN, MAF, CHN, CHF, CXN, CXF, NON, NOF, TVN, TVF, OLN, OLF, SIL	Yes; Signal-to-Noise Ratios	No	No	2	7	Home	-
Brito, Troller-Renfree, Leon-Santos, Isler, Fifer, & Noble	2020	94	0.76	TD	Multilingual	Caucasina/White, African American/Black, Asian/Pacific Islander, Mixed, Did not provide response	Yes	Observational	Cross-sectional design	Assessment	AWC, CV, CT	No	No	No	1	10.89	Home	-
Brushe, Lynch, Reilly, Melhuish, & Brinkman	2020	245	0.48	TD	English	-	Yes	Observational	Prospective cohort study	Assessment	AWC, CV, CT	No	No	No	2	16	Home	-
Brushe, Lynch, Reilly, Melhuish, Mittinty, & Brinkman	2021	265	0.50	TD	English	-	Yes	Observational	Prospective cohort study	Assessment	AWC, CV, CT	No	No	No	3	16	Home	-
Burgess, Audet, & Harjusola-Webb	2013	10	4.25	ASD	-	Caucasian/White, Hispanic	Yes	Experimental	Exploratory study	Assessment	AWC	No	No	No	3.1	8.95	Home, Classroom	-
Carr, Xu, & Yoshinaga-Itano	2014	83	2.38	Deaf/HH/HL	-	-	No	Observational	-	Assessment	CV	NO	No	No	1		-	-
Caskey	2011	36	0.71	Pre-term Infant	English, Spanish, unknown	African American/Black, Hispanic, White	Yes	Observational	Prospective cohort study	Assessment	AWC, CV, CT	No	No	No	2	16	NiCU	-
Caskey, Stephens, Tucker, & Vohr	2014	36	0.71	Pre-term Infant	English, Spanish, Unknown	African American/Black, Hispanic, White, Missing	Yes	Observational	Prospective cohort study	Assessment	AWC, CV, CT	No	No	No	2	16	NiCU	-
Charlton & Law	2014	14	5.50	TD	-	-	No	Experimental	-	Assessment	CV, CT	No	No	No	1	0.17	Classroom	-
Charron, Fitzpatrick, McSweeney, Rabjohn, Somerville, & Steacie	2016	5	3.66	Deaf/HH/HL	English	-	No	Observational	-	Assessment	TVN, SIL, NON, NOF, MAF, MAN, FAF, FAN, CV, CT, AWC	No	No	No	2	16	Home	-
Christakis, Gilkerson, Richards, Zimmerman, Garrison, Xu, Gray, & Yapanel	2009	329	2.08	-	English	White, Hispanic, African American, American Indian, Asian/Pacific Islander, Other, Unknown	Yes	Observational	Prospective, population-based observational study	Assessment	AWC, CV, CT	No	No	No		14	Home	-
Christakis, Lowry, Goldberg, Violette, & Garrison	2019	61	0.58	TD	Spanish, English, other	Asian, Black, White, Other/Native American, Missing data, more than one race	Yes	Experimental	Pre-post study	Feedback	AWC, CV, CT	No	No	No	2	16	Home	-
Clemens & Kegel	2021	43	1.08	-	-	-	Yes	Observational	Repeat measures design	Assessment	AWC, CV, CT	No	No	No	2	10	Home	-
Clifford, Stockdale, Coyne, Rainey, & Benitez	2021	269	1.42	-	English, bilingual non-specified	Latino, Asian, African American/Black, Caucasian/White, Mixed Race, and Other	Yes	Observational	Correlational study	Assessment	AWC, CV, CT, vocal productivity score, AVA	No	No	No	1	12	Home	-
d'Apice, Latham, & von Stumm	2019	107	2.77	-	English	-	No	Observational	Cross-sectional	Assessment	AWC	No	No	Yes	3	5	Home	-
Degotardi, Han, & Torr	2018	57	1.48	-	-	-	Yes	Observational	-	Assessment	AWC, CV	No	No	No	1	3	Classroom	-
Donnelly & Kidd	2021	122	1.38	TD	Australian English	-	No	Observational	Longitudinal design	Assessment	AWC, CV, TVN, CT	No	No	No	3	16	Home	-

Duncan, King, Finders, Elicker, Schmitt, & Purpura	2020	44	4.77	-	-	White, African American, Hispanic, and other	Yes	Observational	Repeat measures design	Assessment	AWC, CV, CT	No	No	No	2	6.38	Classroom	LENA SP
Dwyer, Jones, Davis, Kitamura, & Ching	2019	50	0.66	TD	English	White/Cucasian	Yes	Observational	Longitudinal design	Assessment	AWC, CV, CT	No	No	No	2	12.5	Home	-
Dykstra, Sabatos-DeVito, Irvin, Boyd, Hume, & Odom	2012	40	3.95	ASD	-	White, Black, Asian. Ethnicity: Hispanic, Not-Hispanic	No	Observational	Descriptive study	Assessment	AWC, CV, CT	No	No	No	2	5.3	Classroom	-
Elmquist, Finestack, Kriese, Lease, & McConnell	2021	56	1.71	-	Russian, Bilingual: Spanish and English, Bilingual: other	Asian/Asian-American, Black/African American, Hispanic/Latino, White/Caucasian, Multi	No	Experimental	Nonequivalent group design	Feedback	AWC, CV, CT	No	No	No	13	12	Home	LENA Start
Ferjan Ramirez, Lytle, & Kuhl	2020	71	0.50	TD	English	-	No	Experimental	Randomized control trial	Feedback	AWC, CT, CV	No	Yes	No	4	12.82	Home	-
Fields-Olivieri & Cole	2019	25	1.46	TD	English	Caucasian/White, Not Caucasian/White	No	Observational	-	Assessment	CRY, CV, AWC	Yes; No Vocal Communication	No	No	1	10	Home	-
Fink, Browne, Kirk & Hughes	2020	93	0.35	-	English	Caucasian/White, Asian, African American/Black, Other	No	Observational	-	Assessment	FAN, MAN, CT	No	Yes	No	1	15.42	Home	-
Ganek, Nixon, Smyth, & Eriks-Brophy	2019	55	2.75	TD, Deaf/HH/HL	English or Vietnamese	-	Yes	Observational	Embedded mixed methods	Assessment	CT	No	No	No	3		Home	-
Ganek, Smyth, Nixon, & Eriks-Brophy	2018	55	2.88	TD, Deaf/HH/HL	English or Vietnamese	-	Yes	Observational	Cross-comparison design	Assessment	CT	No	No	No	3	14	Home	-
Garcia-Sierra, Ramirez-Esparza, & Kuhl	2016	54	1.04	TD	English and/or Spanish	-	Yes	Observational	-	Assessment	AWC	No	Yes	No	4	8	Home	-
Gilkerson, Richards, & Topping	2017	146	1.79	TD	English	-	Yes	Observational	Longitudinal design	Assessment	AWC, CT	No	No	No	6	12	Home	-
Gilkerson, Richards, & Topping	2017	98	3.77	TD	English	-	Yes	Observational	-	Assessment	AWC, CV, CT	No	No	Yes	1	16	Home	-
Gilkerson, Richards, Warren, Montgomery, Greenwood, Oller, Hansen, & Paul	2017	329	2.08	TD	English	Caucasian, Latino or Hispanic, African American, Native American, Asian, Other, Not specified	Yes	Observational	Semilongitudinal data	Assessment	AWC, CV, CT	No	No	Yes	4	12	Home	-
Gilkerson, Richards, Warren, Oler, Russo, & Vohr	2018	72	1.15	TD	English	-	Yes	Experimental	-	Feedback	AWC, CT	No	No	No	10	16	Home	-
Gomez & Strasser	2020	43	1.51	-	-	-	Yes	Observational	Longitudinal design	Assessment	AWC, CT, CV	No	No	No	2	10	Home	-
Greenwood, Thiemann-Bourque, Walker, Buzhardt, & Gilkerson	2011	30	1.30	TD	English	European American, African American, and Hispanic, Asian, Pacific Islander, and Multi-race	No	Observational	A prospective longitudinal, cross-sectional design	Assessment	AWC, CV, CT	No	No	Yes	29	12	Home	A prototype version of the LENA System
Ha & Oller	2021	20	0.41	TD, Cleft Lip	Korean	-	No	Experimental	Longitudinal design	Assessment	AWC, CT, CV	No	No	No	5	12	Home	-
Hersey, Hoffman, Tucker, & Vohr	2021	29	0.01	-	-	White, Black, Hispanic, Other	No	Experimental	Prospective pilot cohort intervention study	Feedback	AWC, CV, CT	No	No	No	2	16	NiCU	-
Hoffman, Hersey, Tucker, & Vohr	2020	108	0.01	-	English	White, African American/Black, Hispanic/Latino, other	Yes	Experimental	randomized control trial	Feedback	AWC, CV, CT	No	No	No	4	15.8	Home, NiCU	-
Irvin, Bard, Wallisch, & Little	2018	1	5.17	TD	-	-	Yes	Observational	case-study design	Assessment	AWC, CV, CT	No	No	No	1	5.25	Home, Community	-
Irvin, Crutchfield, Greenwood, Simpson, Sangwan, & Hansen	2017	1	5.00	LD	-	-	No	Observational	case-study design	Assessment	AWC, CT, CV, CXN	No	No	No	1	5.58	Classroom	-
Irvin, Hume, Boyd, McBee, & Odom	2013	67	4.00	ASD	-	Race: Asian, Black, White. Ethnicity: Hispanic (11)	No	Observational	-	Assessment	AWC	No	No	No	1	2.8	Classroom	-
Jackson & Callender	2014	57	3.75	TD	Bilingual: Spanish and English	Mexican, European American, Caribbean American	Yes	Observational	-	Assessment	CV	No	No	No	1	10.8	Home, Classroom	-
Johnson, Caskey, Rand, Tucker, & Vohr	2014	33	0.01	Pre-term	English	white non-Hispanic, Black non-Hispanic, Hispanic, Multiracial/other	Yes	Observational	prospective cohort study	Assessment	AWC, FAN, MAN, CV, CT	No	No	No	4	15.4	Home, NiCU	-
King, Camacho, Montez, Humphreys, & Gotlib	2021	51	0.46	-	English, Spanish, French, Mandarin, Cantonese, Danish, Polish, Hindi, Tamil	Hispanic or Latinx, White, Asian or Asian American, Black of African American, Native Hawaiian or Pacific Islander, Other race	Yes	Observational	Correlational study	Assessment	AWC, CT, CV	No	No	No	1	8	Home	-
King, Querdasi, Humphreys, & Gotlib	2020	100	0.56	TD	English	white, asian or asian american, black or African American, Native Hawaiian or Pacific Islander, other race; Ethnicity: hispanic/Latinx	Yes	Observational	Longitudinal design	Assessment	AWC, CT, CV	Yes; Consistency of Exposure ot AWC and CT	Yes	No	1	8	Home	-
Kisshida & Kemp	2020	6	2.36	Deaf/HH/HL	culturally and linguistically diverse non-English	-	No	Experimental	AB single case experimental design	Feedback	AWC, CV, CT	No	No	No	6	16	Home	-

Romeo, Leonard, Robinson, West, Mackey, Rowe, & Gabrieli	2018	40	5.78	TD	English	-	No	Observational	Correlational study	Assessment	AWC, CV, CT	No	No	No	2	16	Home	-
Romeo, Segaran, Leonard, Robinson, West, Mackey, Yendiki, Rowe, & Gabrieli	2018	36	5.00	TD	English	-	Yes	Observational	Correlational study	Assessment	AWC, CV, CT	No	No	No	2	16	Home	-
Rufsvold, Wang, Hartman, Arora, & Smolen	2018	41	3.90	TD, Deaf/HH/HL	English	-	Yes	Observational	-	Assessment	AWC, CT, CV	No	No	No	2	16	Home	-
Sacks, Shaw, Repplinger, Leffel, Sapolich, Suskind, Tannenbaum, & Suskind	2014	11	2.71	Deaf/HH/HL	English as second language	White, Latino, African American, Asian American or Pacific Islander, Native American or Alaskan Native	Yes	Observational	-	Feedback	AWC, CT, CV	No	No	No	5	16	Home	-
Saetre-Turner, Williams, & Quail	2015	10	3.15	TD, Deaf/HH/HL	English	-	Yes	Observational	-	Assessment	AWC, CT, CV	No	No	No	1	5	Home	-
Seidl, Cristia, Soderstrom, Ko, Abel, Kellerman, & Schwichtenberg	2018	36	1.50	At-risk of ASD	English	White non-Hispanic or Latino, Black non-Hispanic or Latino, Black Hispanic or Latino, Multiracial non-Hispanic or Latino, Multiracial Hispanic or Latino, Unknown or unreported	Yes	Observational	Prospective design	Assessment	CV, AVA score, CT	Yes; Acoustic-Prosodic Alignment	Yes	No	1	6	Home	-
Shapiro, Hippe, & (Ferjan) Ramirez	2021	23	0.50	TD	English	White, Unknown, Mixed race	No	Observational	Longitudinal	Assessment	AWC, FAN, MAN, CV	No	No	No	5	12.8	Home	-
Soderstrom & Wittebolle	2013	11	1.80	-	English	-	Yes	Observational	-	Assessment	AWC, CV, CT	No	Yes	No	3	6	Home, Childcare	LENA software suite (version 3.1.6)
Soderstrom, Grauer, Dufault, & McDivitt	2018	45	2.00	-	English or French	-	No	Observational	-	Assessment	AWC	No	No	No	6	6	Home, Childcare	LENA pro
Sulek, Smith, Bent, Hudry, Trembath, Vivanti, & Dissanayake	2020	99	2.63	ASD	-	-	No	Observational	Correlational study	Assessment	CV, CT	Vocalization Ratio	No	No	2	1	Clinic	LENA pro
Sultana, Wong, & Purdy	2020	20	3.50	TD	English	-	Yes	Observational	-	Assessment	AWC, CT	No	Yes	No	2	12.17	Home, Classroom	-
Sundqvist, Koch, Thornberg, Barr, & Heimann	2021	92	2.09	TD	Swedish	-	Yes	Observational	-	Assessment	AWC, CV, CT	No	No	No	1	16	Home	-
Suskind, Graf, Leffel, Hernandez, Suskind, Webber, Tannenbaum, & Nevins	2016	17	1.70	TD	English, bilingual	Caucasian, African American, Asian, Hispanic, multiethnic, declined to state	No	Experimental	Prospective case-crossover design	Feedback	AWC, CT	No	No	No	8	12	Home	-
Suskind, Leffel, Graf, Hernandez, Gunderson, Sapolich, Suskind, Leininger, Meadow, & Levine	2016	23	0.19	TD	-	Black, White	Yes	Experimental	Randomized controlled trial	Feedback	AWC, CT, CV	No	No	No	14	10	Home	-
Suskind, Leffel, Hernandez, Sapolich, Suskind, Kirkham, & Meehan	2013	31	4.50	Deaf/HH/HL	Spanish and English	Black, Hispanic	Yes	Experimental	Quasiexperimental design	Feedback	AWC, CT	No	No	No	16	10	Home	-
Swanson, Donovan, Paterson, Wolff, Parish-Morris, Meera, Watson, Estes, Marrus, Elison, Shen, McNeilly, MacIntyre, Zwaigenbaum, John, Botteron, Dager, Piven, & IBIS Network	2019	59	6.49	At-risk of ASD	English	White, African American, Asian, More than one race, Did not answer; ETHNICITY: not hispanic, Hispanic, Did not answer	Yes	Observational	-	Assessment	CV, CT, AWC	No	No	No	1	8	Home	LENA Pro software suite V3.3.4
Swanson, Shen, Wolff, Boyd, Clements, Rehg, Elison, Paterson, Parish-Morris, Chappel, Hazlett, Emerson, Botteron, Pandey, Schultz, Dager, Zwaigenbaum, Estes, & Piven	2018	96	0.75	At-risk of ASD	-	-	Yes	Observational	Prospective design	Assessment	AWC, CT	No	No	No	2	8	Home	LENA Pro
Thiemann-Bourque, Warren, Brady, Gilkerson, & Richards	2014	18	2.63	TD, Down Syndrom	English	-	Yes	Observational	Cross-sectional	Assessment	AWC, CV, CT	No	Yes	Yes	2	12	Home	-
Trembath, Westerveld, Teppala, Thirumanickam, Sulek, Rose, Tucker, Paynter, Hetzroni, Keen, & Vivanti	2019	23	4.13	ASD	English, Other	-	No	Observational	Longitudinal cohort design	Assessment	CV	Vocalization Ratio	No	No	10	3	Classroom	-
Tulviste & Tamm	2021	22	3.11	-	Estonian	-	Yes	Observational	Two-wave longitudinal study	Assessment	AWC, CV, CT	No	Yes	No	2	15	Home	-
VanDam, Ambrose, & Moeller	2012	30	2.50	TD, Deaf/HH/HL	English	Race: Caucasian, Black, Other, Did not reply; Ethnicity: Hispanic, Not hispanic, ethnicity not provided	No	Observational	Group comparison	Assessment	AWC, CT	No	No	No	1	12	Home	-
VanDam, Thompson, Wilson-Fowler, Campanella, Wolfenstein, & Palma	2021	26	2.58	TD	English	Black, Hispanic/Latino, White, Asian/Pacific Islander	Yes	Observational	-	Assessment	CT, FAN, MAN, CHN	Yes; Conversation Initiation Counts	No	No	7.1	12	Home	LENA Pro
Vohr, Topol, Watson, St. Pierre, & Tucer	2013	56	7.50	TD, Deaf/HH/HL	English, Spanish, Other	White	Yes	Observational	Prospective longitudinal study	Assessment	CV, CT, AWC	No	No	No	1	12	Home	-
Wang, Cooke, Reed, Dilley, & Houston	2021	41	1.70	TD, Deaf/HH/HL	English	-	Yes	Observational	Longitudinal	Assessment	AWC, CV, CT, TVN, OLN, NON	No	No	No	8	12	Home	-
Warlaumont, Richards, Gilkerson, & Oller	2014	183	4.67	TD, ASD	-	-	Yes	Observational	Correlational study	Assessment	CV, CRY, AWC	Yes; Contingency of Adults' Responses to Child's Vocalization	No	No	4.7	12	Home, Classroom, Clinic	-
Warren, Gilkerson, Richards, Oller, Xu, Yapanel, & Gray	2010	104	2.67	TD, ASD	English	-	Yes	Observational	-	Assessment	AWC, CT, CV	No	Yes	No	8	12	Home, Childcare	-

Klein, Wu, Stangl, & Bentler	2018	22	73.00	Deaf/HH/HL, other old age	-	-	No	Experimental	Cross-over design	Assessment	NON, FAN, MAN, FAF, MAF, AWC, TVN, SIL	No	No	Yes	7	11.48	Home	-
Knight-McKenna, Hollingsworth, & Esposito	2020	22	0.43	-	Spanish, Bilingual: Spanish and English	Black/African American, White, Other: Hispanic, Latino, and/or Mexican, Other: not specified, no response; Ethnicity: Hispanic, latino, or Spanish, Not Hispanic, Latino, or Spanish	Yes	Experimental	Mixed-methods	Feedback	AWC, CT, CV	No	No	No	11.3	15.7	Home	-
Ko, Seidl, Cristia, Reimchen, & Soderstrom	2016	13	1.70	-	English	-	No	Observational	Correlational study	Assessment	FAN, CHN	Yes; Pitch and Speaking Rate	Yes	No	4	10	Home	-
Kristensen, Sundby, Hauge, & Lofkvist	2020	17	2.69	TD, Deaf/HH/HL	Norwegian	-	Yes	Observational	A cross-sectional pilot study	Assessment	FAN, FAF, MAN, MAF	No	Yes	Yes	1	12.46	Home	LENA pro
Larson, Barrett, & McConnell	2020	38	2.49	-	English	White, Black/African American, Hispanic/Latino/a, Asian, Native American/Alaskin Native, Other	Yes	Observational	-	Assessment	AWC, CT, CV	No	No	No	2	10.2	Home, Childcare	-
Leung, Hernandex, & Suskind	2020	157	1.19	-	English	European American, non-Hispanic, African American non-Hispanic, -	Yes	Experimental	Matched pairs parallel group randomized control trial	Feedback	AWC, CT	No	No	No	2	8	Home	-
Li, Vikani, Harris, & Lin	2014	37	75.90	Other, old age	-	African American	Yes	Observational	-	Assessment	AWC, MAN, FAN, MAF, FAF, SIL, TVN, TV duration	No	No	Yes	1	13.22	Home	-
List, Pernaudet, & Suskind (Study 2)	2021	91	2.25	TD	Spanish	Hispanic, Latinx, White	Yes	Experimental	Randomized control trial	Feedback	AWC, CT, CV	No	No	No	2	8	Home	-
Liszka, Heiny, Smith, Schlaggar, Mathur, & Pineda	2020	73	0.54	At-risk of LD	English	African American, -	Yes	Observational	-	Assessment	MAN, FAN, MAF, FAF, TVN, NON, SIL	No	No	No	1	16	home, NiCU	-
Liszka, Smith, Mathur, Schlaggar, Coldtz, & Pineda	2019	98	0.01	Pre-term	English	African American, -	Yes	Observational	-	Assessment	Avg. decibel level, MAN, FAN, MAF, FAF, AWC, TVN, NON, SIL	No	No	No	1	16	NiCU	-
Little, Rojas, Bard, Luo, Irvin, & Rous	2019	10	5.69	TD, ASD	English	White non-Hispanic, Asian non-Hispanic	Yes	Observational	-	Assessment	CV, CT, AWC	No	No	No	2	12	Home, Community	-
Ma, Johnsson, Feng, Weisber, Shao, Yao, Zhang, Dill, Guo, Zhang, Friesen, & Rozelle	2021	38	2.05	-	Mandarin	-	Yes	Observational	Correlational study	Assessment	AWC, CT, CV	No	No	No	1	12	Home	-
Marchman, Martinez, Hurtado, Gruter, & Fernald	2017	18	3.15	TD	Bilingual: Spanish and English	Latino/ Mexican	Yes	Observational	-	Assessment	AWC	Yes; Child Directed Speech in Spanish and English	No	No	1	8.6	Home, Community	-
McGillion, Pine, Herbert, & Mathews	2017	142	0.92	TD	English	-	Yes	Experimental	Randomised controlled trial	Assessment	AWC, CV	No	No	No	2		Home	-
Merz, Maskus, Melvin, He, & Noble	2020	94	7.03	TD	English	Hispanic/Latino, African American, non-Hispanic/Latino, and White, non-Hispanic/Latino, other	Yes	Observational	Cross-sectional	Assessment	AWC, CV, CT	No	Yes	No	1	14.22	Home	-
Nyberg, Rudner, Thornberg, Koch, Barr, Heimann, & Sundqvist	2020	88	0.79	TD	Swedish	-	No	Observational	Longitudinal design	Assessment	AWC, CV, CT, and TVN	No	No	No	1	12	Home	-
Orena, Byers-Heinlein, & Polka	2018	21	0.83	-	Bilingual: French and English	-	No	Observational	-	Assessment	AWC	No	No	No	3	16	Home	-
Pae, Yoon, Seol, Gilkerson, Richards, Ma, & Topping	2016	99	0.83	TD	Korean	-	No	Experimental	Pre- post-test	Feedback	AWC, CT	No	Yes	No	25		Home	-
Parikh & Mastergeorge	2018	43	3.30	Down Syndrom	English	Hispanic or Latino, White, Biracial/multiracial	Yes	Observational	Cross-sectional	Assessment	AWC, CV, CT	No	No	No	1	16	Home	-
Pierce, Reilly, & Nelson	2021	16	0.54	TD	English	White, African American, other; Ethnicity: Hispanic/Latino/Spanish	Yes	Observational	-	Assessment	AWC, CV, CT	No	No	No	2	10.13	Home	-
Pineda, Durant, Mathur, Inder, Walendorf, & Schlaggar	2017	58	0.01	-	-	African American, Not Described	Yes	Observational	Exploratory design	Assessment	MAN, FAN, MAF, FAF, TVN, NON, SIL, AWC, highest and average decibel levels	No	No	No	4	16	NiCU	-
Ramirez, Hippe, & Sapiro	2021	24	0.46	TD	English	White, unknown, Mixed race	No	Observational	Longitudinal design	Assessment	AWC, CV, TVN	No	Yes	No	5	12	Home	LENA pro
Ramirez-Esparza, Garcia-Sierra, & kuhl	2014	26	1.04	TD	English	White, Multi-racial: White and Hispanic, white and Native American/ Eskimo, White Black and Native American	Yes	Observational	Longitudinal design	Assessment	AWC	No	No	No	4	16	Home	-
Reisinger, Shaffer, Pedapati, Dominick, & Erickson	2019	9	3.19	Fragile X Syndrom	-	-	No	Observational	Longitudinal design	Assessment	AWC. CV. CT	No	No	No	1	12	Home	-
Romeo, Leonard, Grotzinger, Robinson, Takada, Mackey, Scherer, Rowe, West, & Gabrieli	2021	52	5.00	TD	Bilingual Spanish and English, Bilingual: Haitian Creole and English, Bilingual: Cape Verdean Creole and English	White/Caucasian, Black/African American, Hispanic/Latinx, Asian, Native American/American Indian, Native Hawaiian/Pacific Islander, Other (self-identified as Cape Verdean)	Yes	Experimental	Randomized control trial	Assessment	AWC, CV, CT	No	No	No	2	16	Home	-

Weil & Middleton	2010	6	2.08	LD	English	-	No	Experimental	Quasi-experimental design with a wait-list control group	Assessment	AWC, CV, CT	No	No	No	2	12	-	-
Weisleder & Fernald	2013	29	1.79	TD	Spanish	Latino	Yes	Observational	-	Assessment	AWC	No	Yes	No	1	7	Home	-
Wiggin, Gabbard, Thompson, Goberis, & Yoshinaga-Itano	2012	8	4.00	Deaf/HH/HL	English	Hispanic, Caucasian	No	Observational	-	Assessment	AWC, CT	No	No	No	1	5.8	Home, Classroom	-
Wood, Diehm, & Callender	2016	81	4.08	TD	Bilingual: Spanish and English, English	Multi-racial: Hispanic/Latin American and White, Black, Hispanic/Latin American, and Asian descent	Yes	Experimental	-	Assessment	AWC, CT, CV	No	No	No	1	10.47	Home, Classroom	-
Xu, Stroud, Jozanovic, Clucas, Son, Koo, Schwarz, Klein, Busman, & Milham Study 1	2018	12	6.50	-	-	-	No	Observational	-	Assessment	VC, Vocalization duration, average decibel levels, CT	No	No	No	4	0.17	Classroom	Lena Pro
Xu, Stroud, Jozanovic, Clucas, Son, Koo, Schwarz, Klein, Busman, & Milham Study 2	2018	12	6.50	Selective Mutism	-	-	No	Experimental	Alternating block design	Assessment	VC, Vocalization duration, CT	No	No	Yes	1	0.17	Research Room	Lena Pro
Zhang, Xu, Jiang, Gilkerson, Xu, Richards, Hamsberger, & Topping	2015	22	2.92	-	Mandarin and Shanghai dialect	Han Chinese	No	Experimental	Pre post-test	Feedback	AWC, CT	No	No	No	24	12	Home	-
Zimmerman Study 1	2009	275	1.77	-	English	Black, Latino, nonblack, Other	Yes	Observational	cross-sectional	Assessment	AWC, CT, TVN	No	Yes	No	4.7	12	Home	-
Zimmerman Study 2	2009	71	2.33	-	English	Black, Latino, nonblack, Other	Yes	Observational	Longitudinal design	Assessment	AWC, CT, TVN	No	Yes	No	6	12	Home	-

APPENDIX C: SYSTEMATIC LITERATURE REVIEW CITATIONS OF INCLUDED STUDIES

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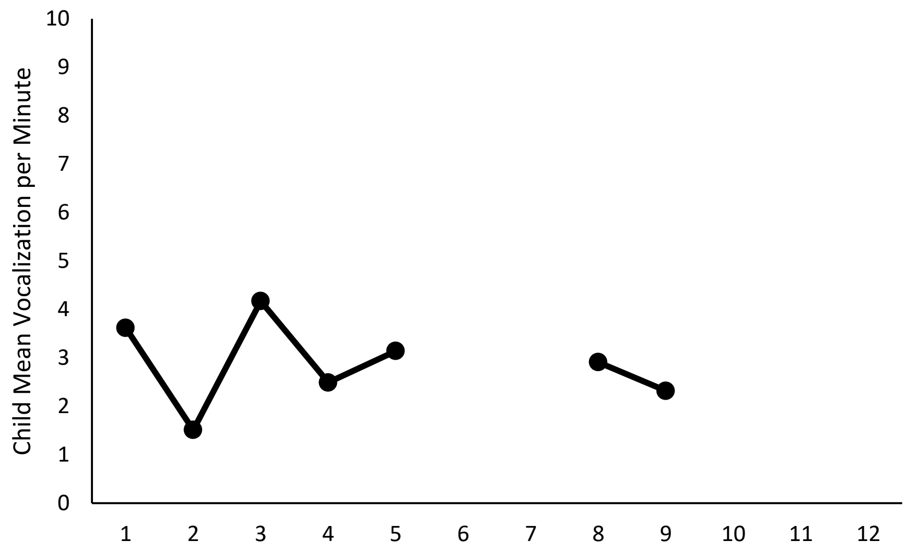
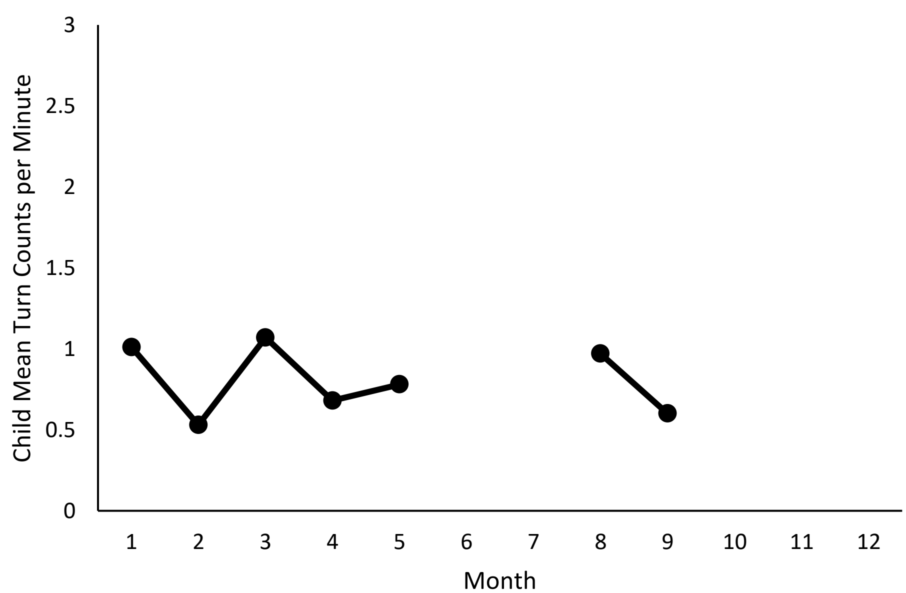
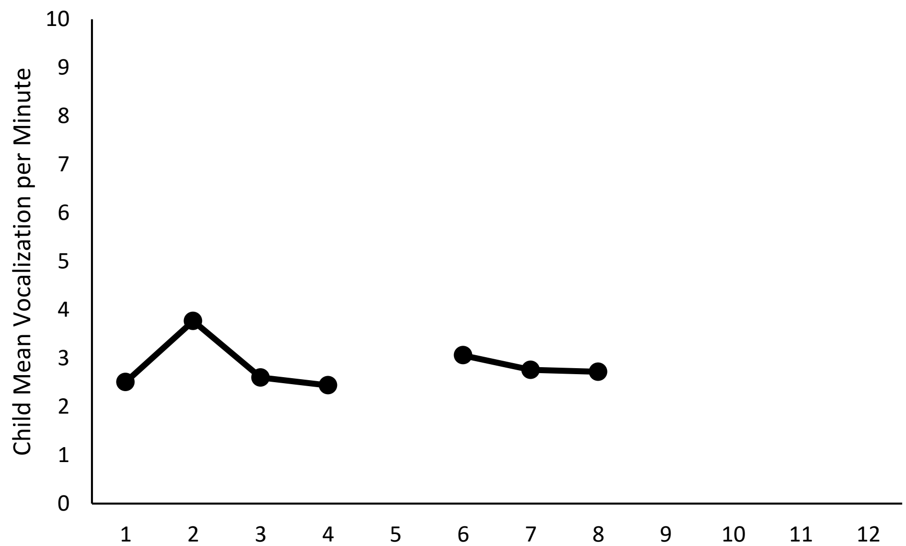
APPENDIX D: INDIVIDUAL CHILD GRAPHS DEPICTING CHANGE IN MEAN CHILD VOCALIZATIONS AND MEAN TURN COUNTS

Child 1.





Child 2.


Child Mean Vocalization per Minute
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3
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8
9
10
1
2
3
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5
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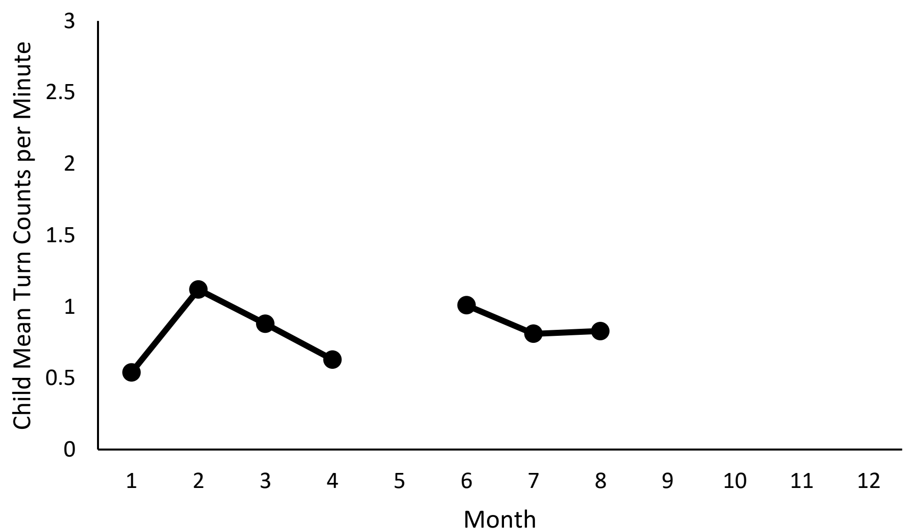
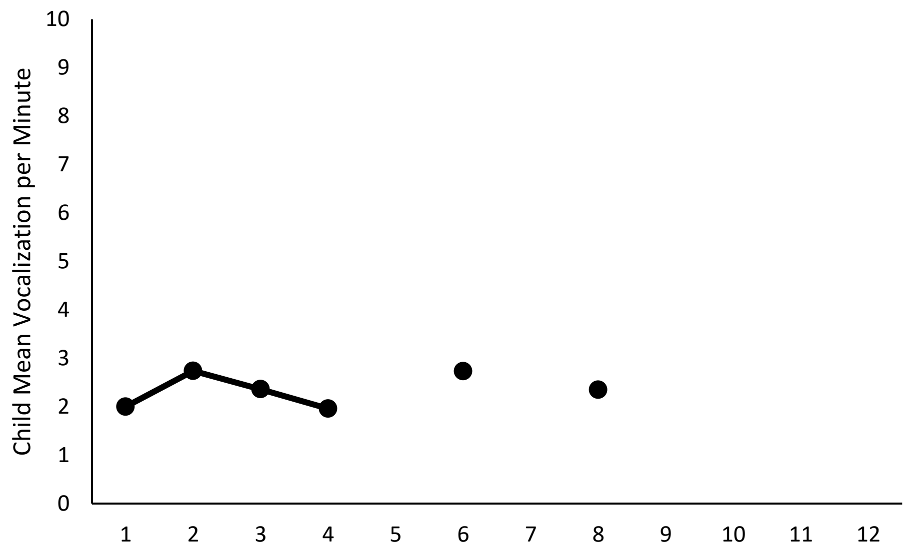
8
9
10
11
12


Child Mean Turn Counts per Minute
0
0.5
1
1.5
2
2.5
3
1
2
3
4
5
6
7
8
9
10
11
12
Month

Child 3.


Child Mean Vocalization per Minute
0
1
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5
6
7
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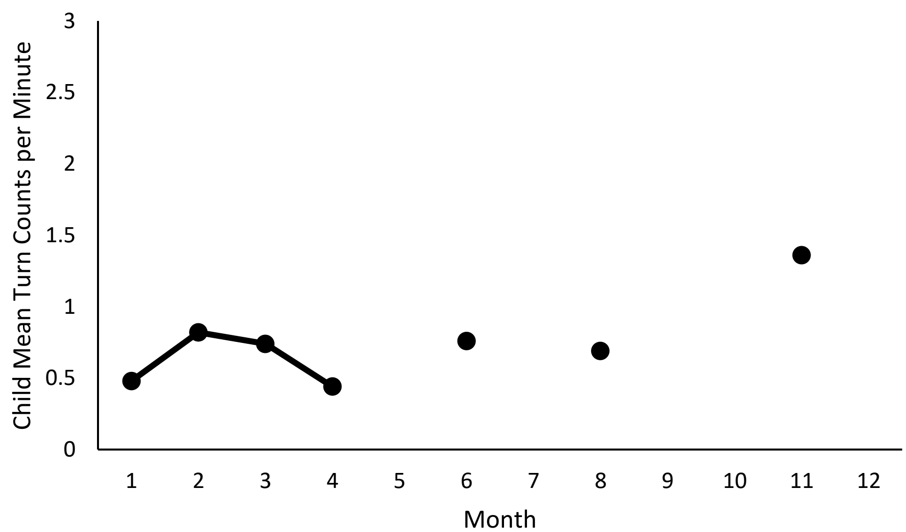
1 2 3 4 5 6 7 8 9 10 11 12


Child Mean Turn Counts per Minute
0
0.5
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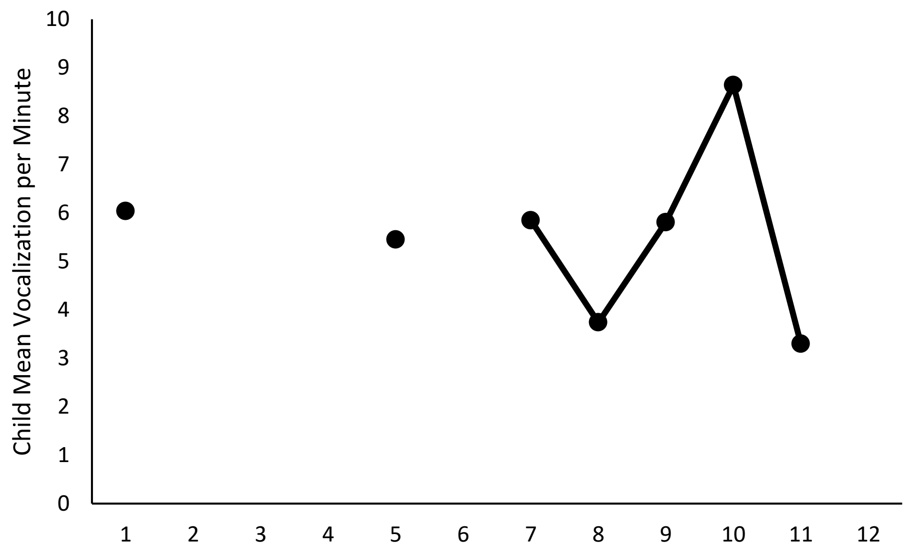
1.5
2
2.5
3
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 4.



Child Mean Vocalization per Minute
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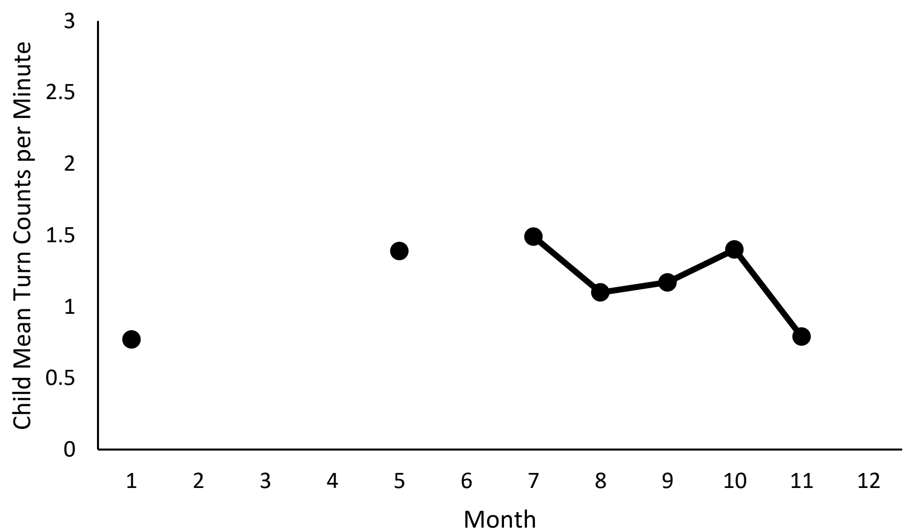

Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
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10
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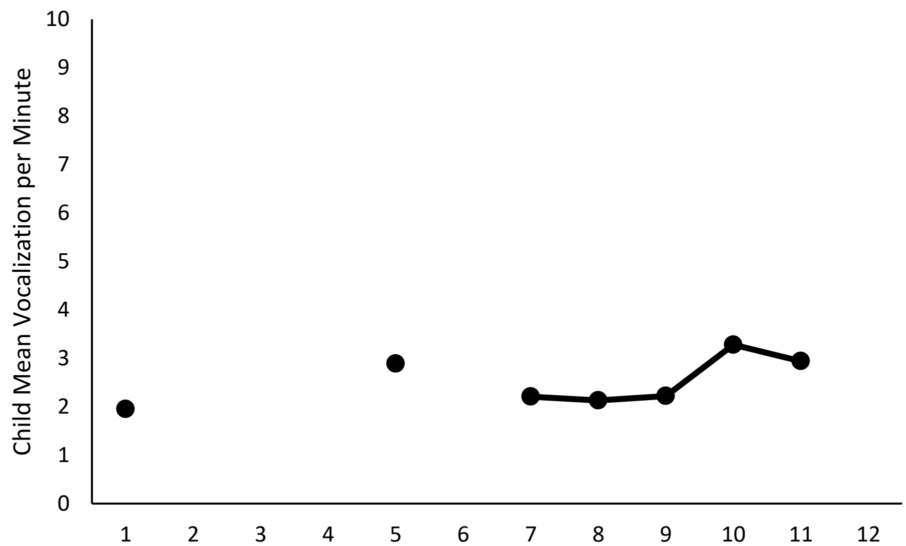
12
Month

Child 5.



Child Mean Vocalization per Minute
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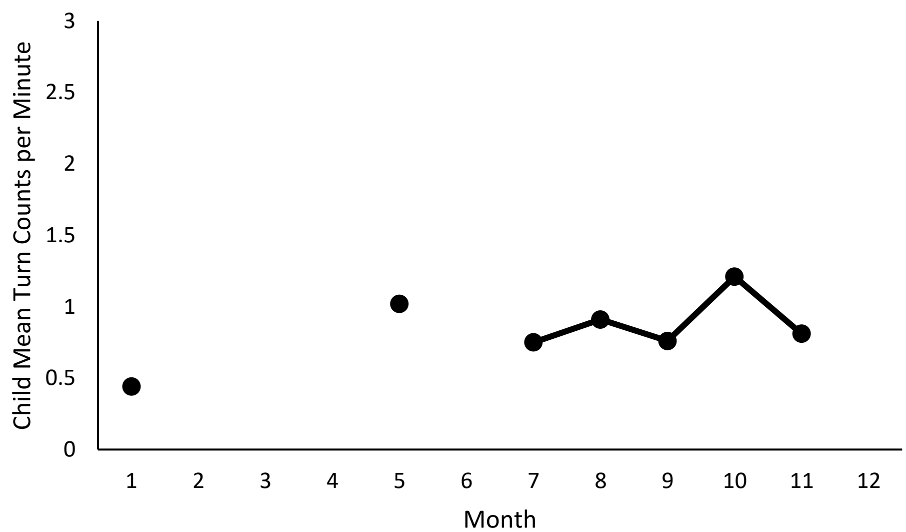
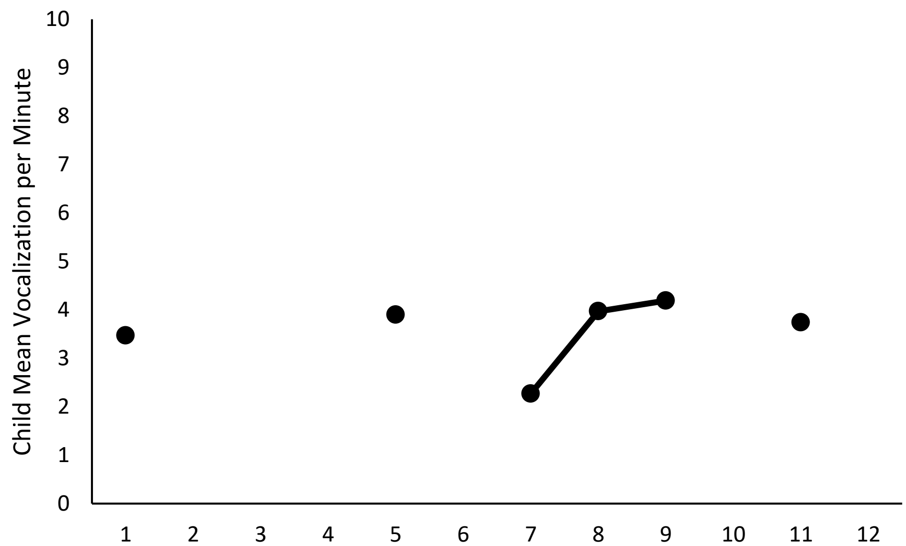
1 2 3 4 5 6 7 8 9 10 11 12



Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
0
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 6.



Child Mean Vocalization per Minute
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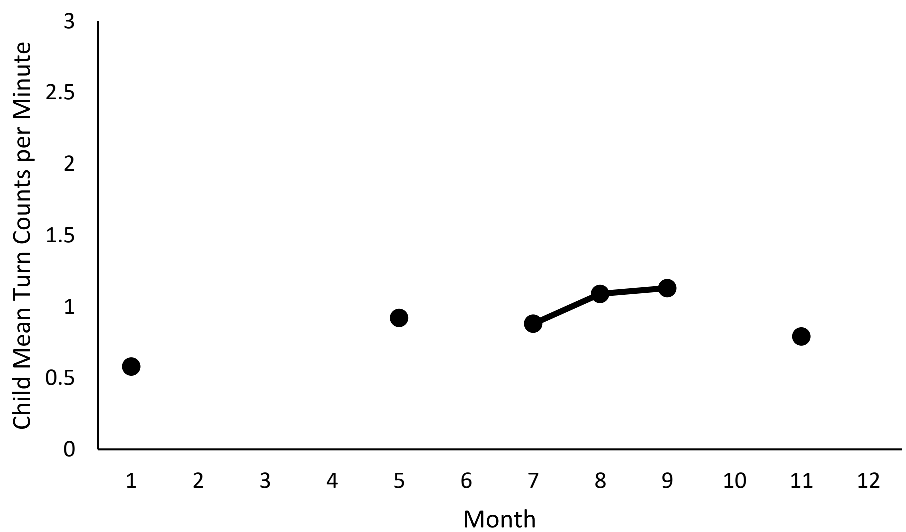
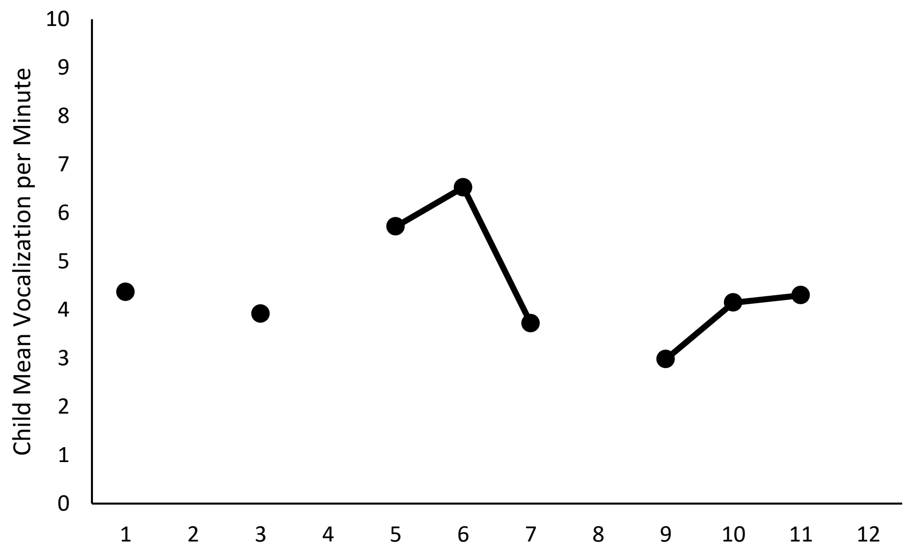
1 2 3 4 5 6 7 8 9 10 11 12



Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
0
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 7.


Child Mean Vocalization per Minute
10
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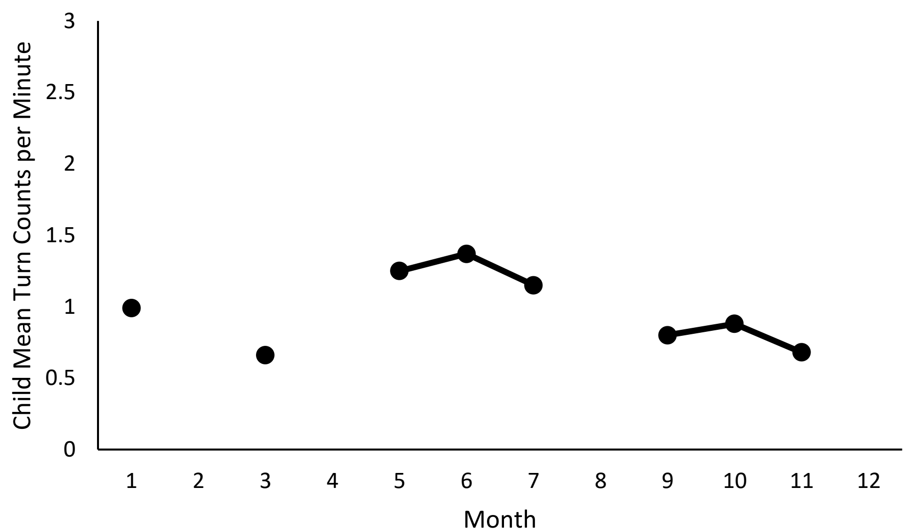
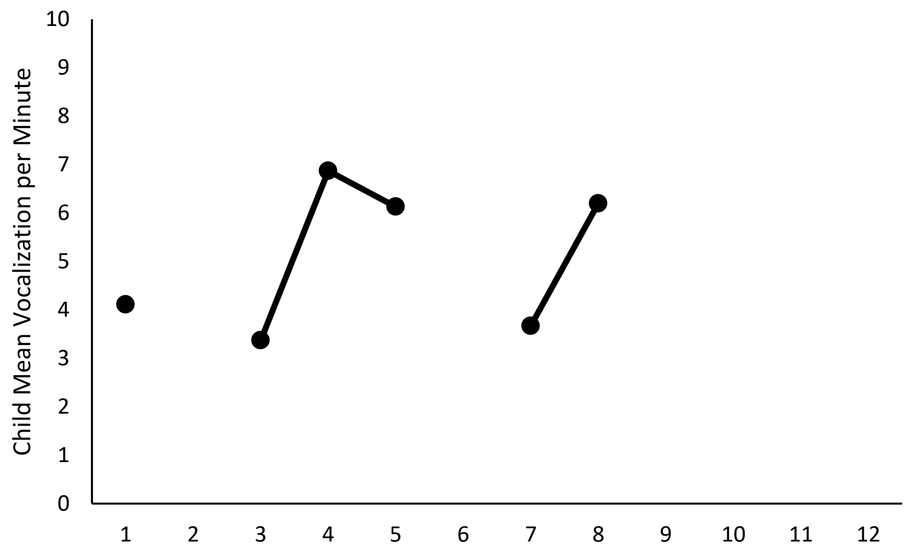
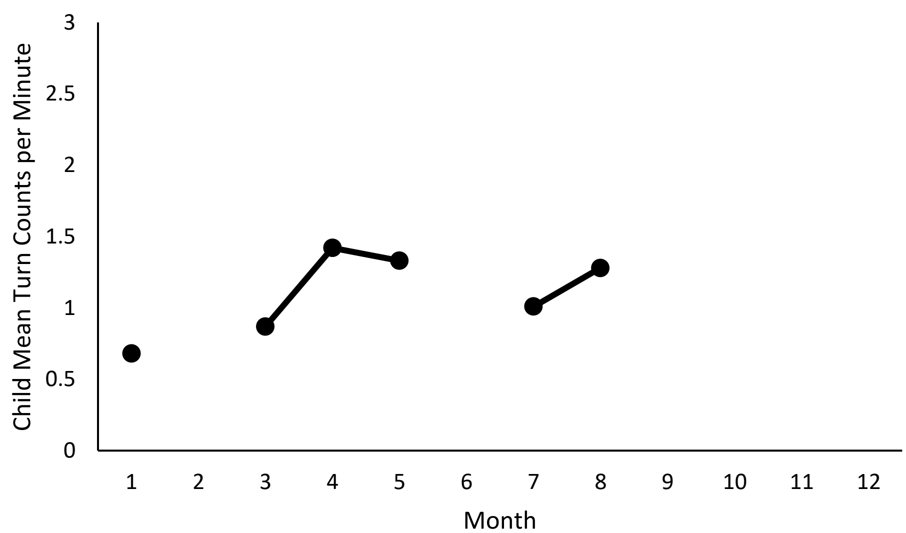
0
1 2 3 4 5 6 7 8 9 10 11 12

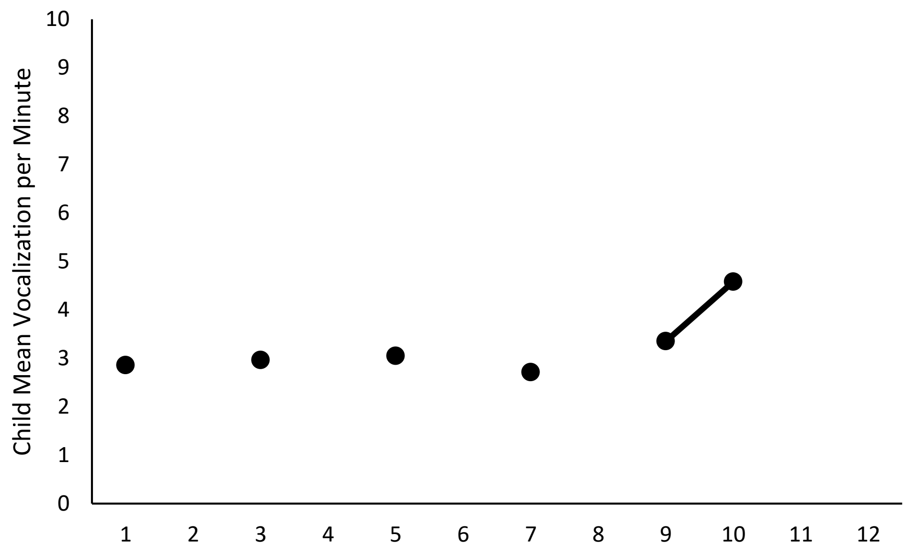

Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
0
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 8.

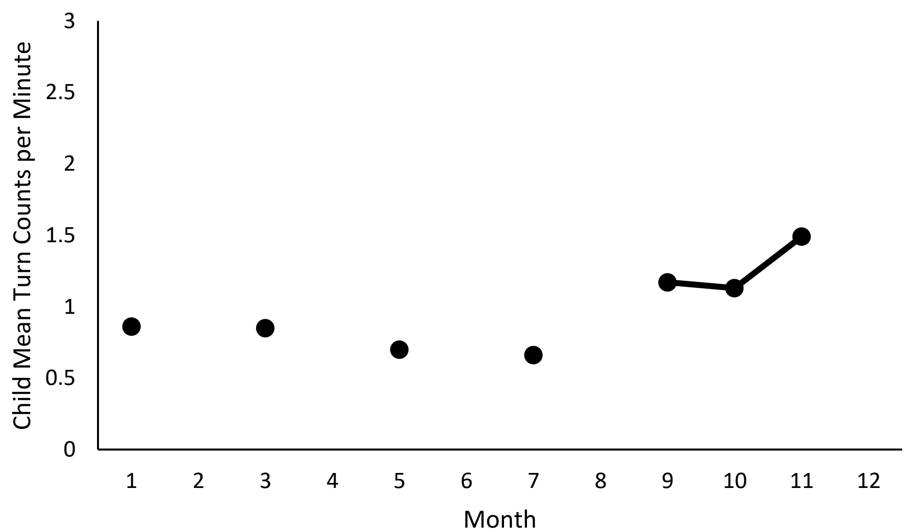

Child Mean Vocalization per Minute
10
9
8
7
6
5
4
3
2
1
0
1 2 3 4 5 6 7 8 9 10 11 12


Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
0
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 9.

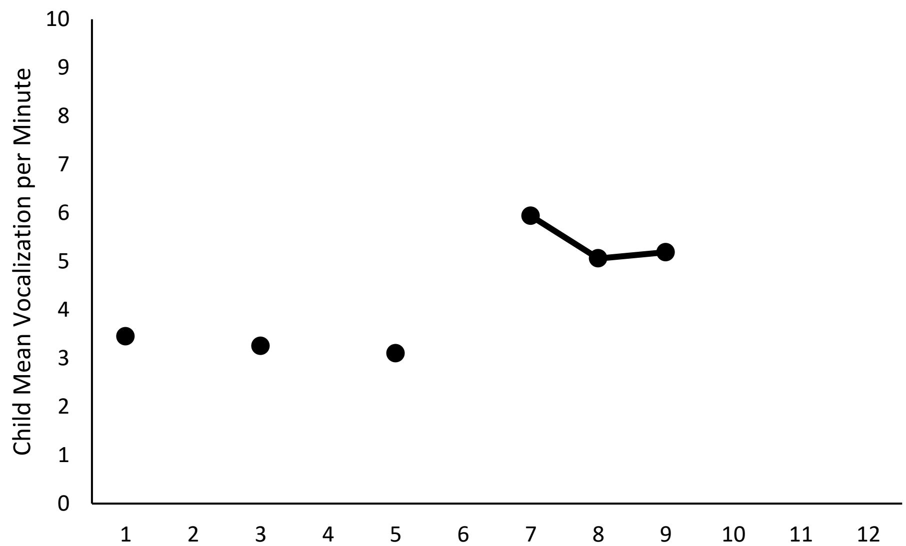


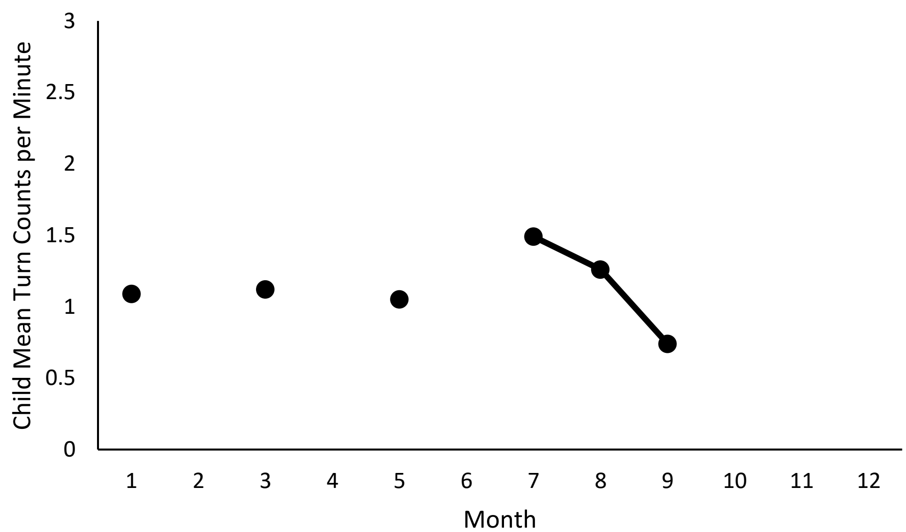
Child Mean Vocalization per Minute
0
1
2
3
4
5
6
7
8
9
10
1 2 3 4 5 6 7 8 9 10 11 12



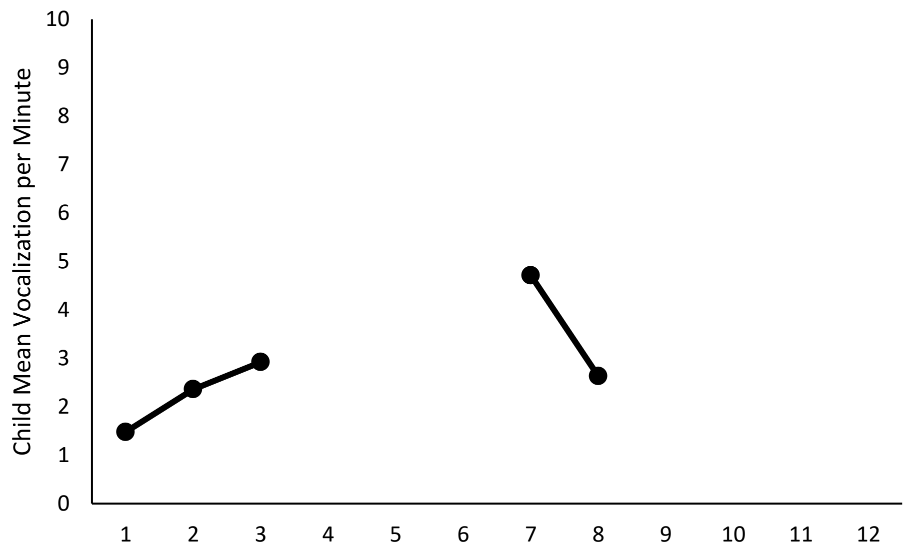
Child Mean Turn Counts per Minute
0
0.5
1
1.5
2
2.5
3
1 2 3 4 5 6 7 8 9 10 11 12
Month

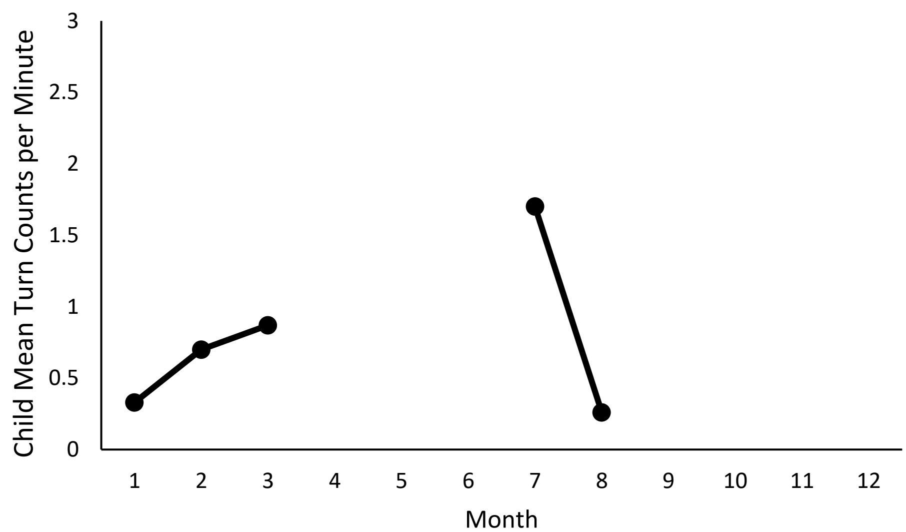
Child 10.


Child Mean Vocalization per Minute
0
1
2
3
4
5
6
7
8
9
10
1 2 3 4 5 6 7 8 9 10 11 12

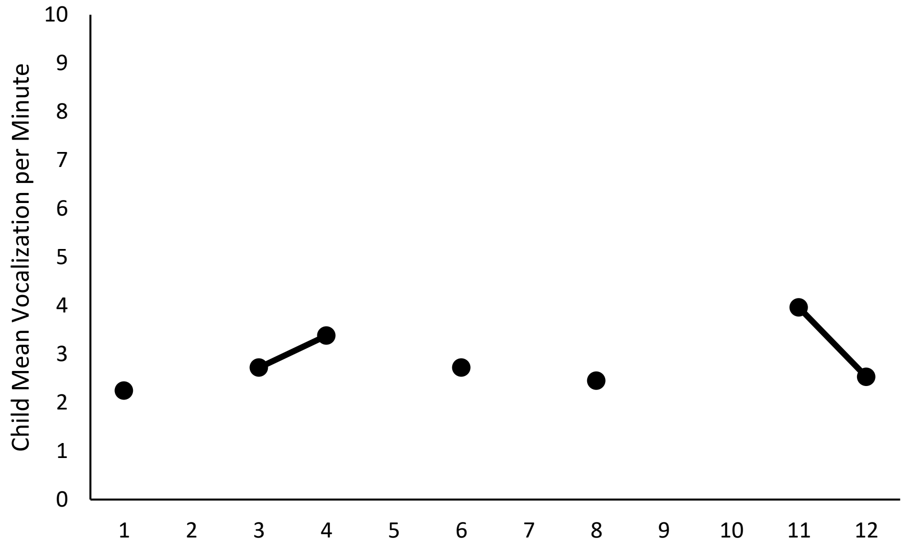

Child Mean Turn Counts per Minute
0
0.5
1
1.5
2
2.5
3
1 2 3 4 5 6 7 8 9 10 11 12
Month

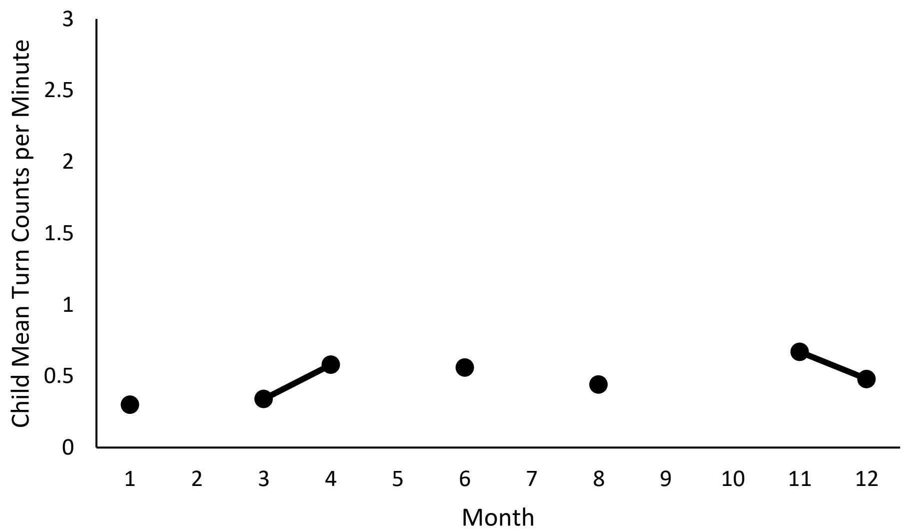
Child 11.


Child Mean Vocalization per Minute
0
1
2
3
4
5
6
7
8
9
10
1 2 3 4 5 6 7 8 9 10 11 12

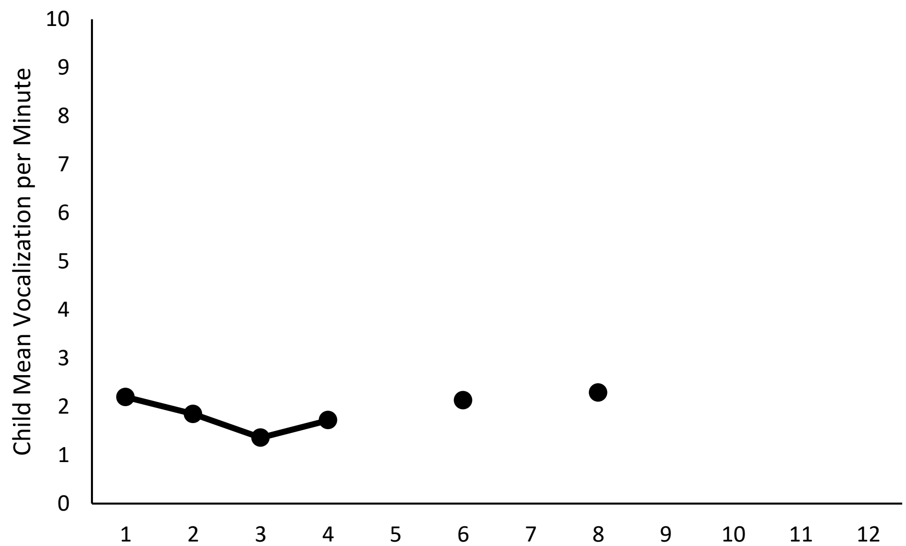

Child Mean Turn Counts per Minute
0
0.5
1
1.5
2
2.5
3
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 12.


Child Mean Vocalization per Minute
0
1
2
3
4
5
6
7
8
9
10
1 2 3 4 5 6 7 8 9 10 11 12


Child Mean Turn Counts per Minute
0
0.5
1
1.5
2
2.5
3
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 13.



Child Mean Vocalization per Minute
10
9
8
7
6
5
4
3
2
1
0
1
2
3
4
5
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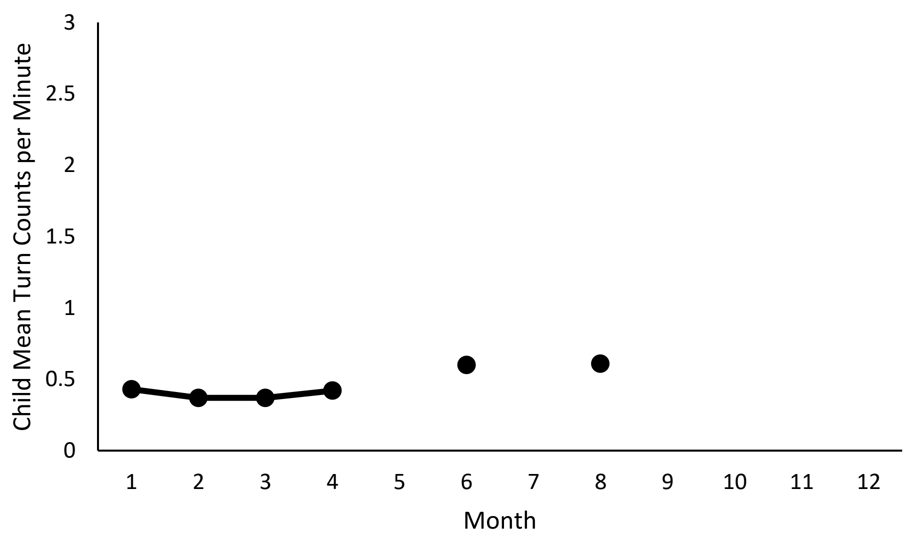
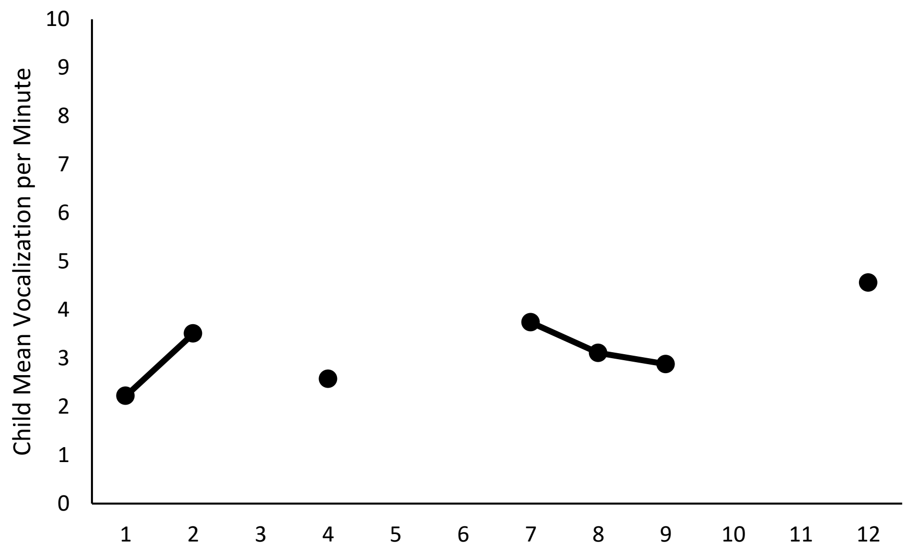
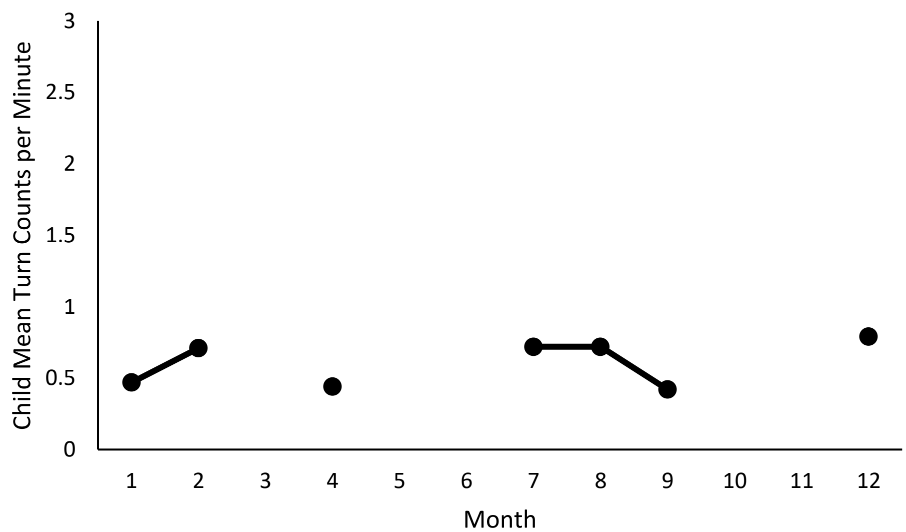
7
8
9
10
11
12



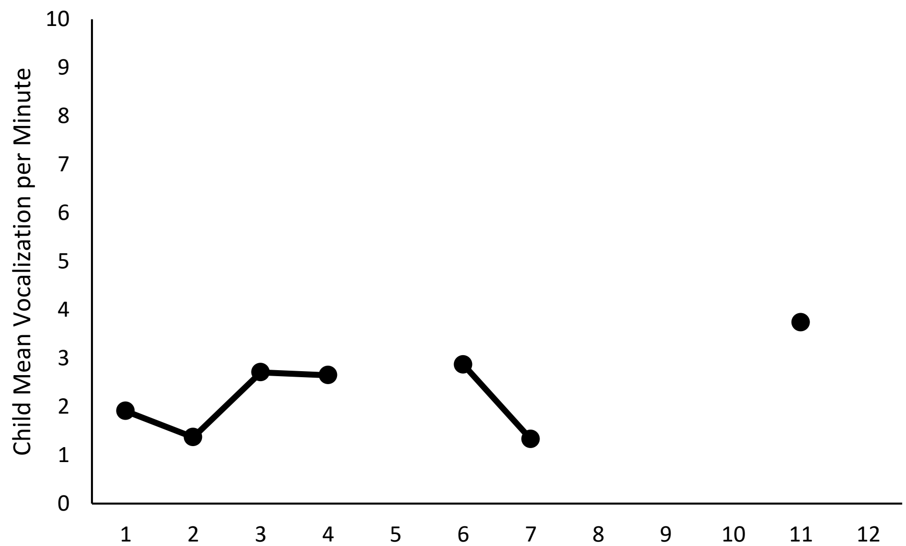
Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
0
1
2
3
4
5
6
7
8
9
10
11
12
Month

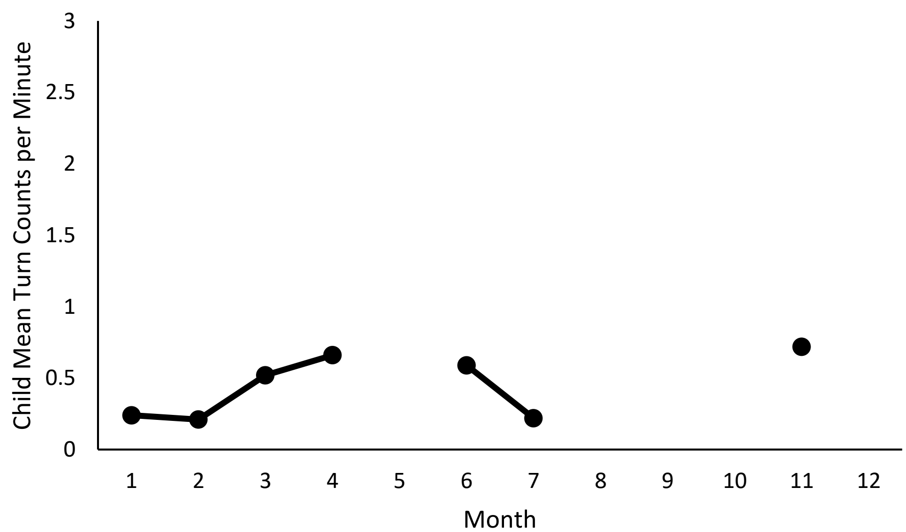
Child 14.


Child Mean Vocalization per Minute
0
1
2
3
4
5
6
7
8
9
10
1 2 3 4 5 6 7 8 9 10 11 12

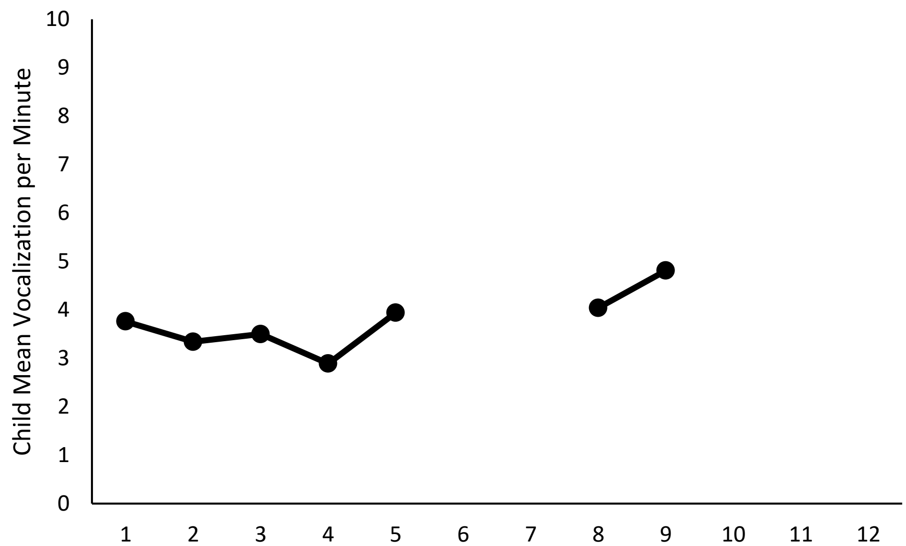

Child Mean Turn Counts per Minute
0
0.5
1
1.5
2
2.5
3
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 15.

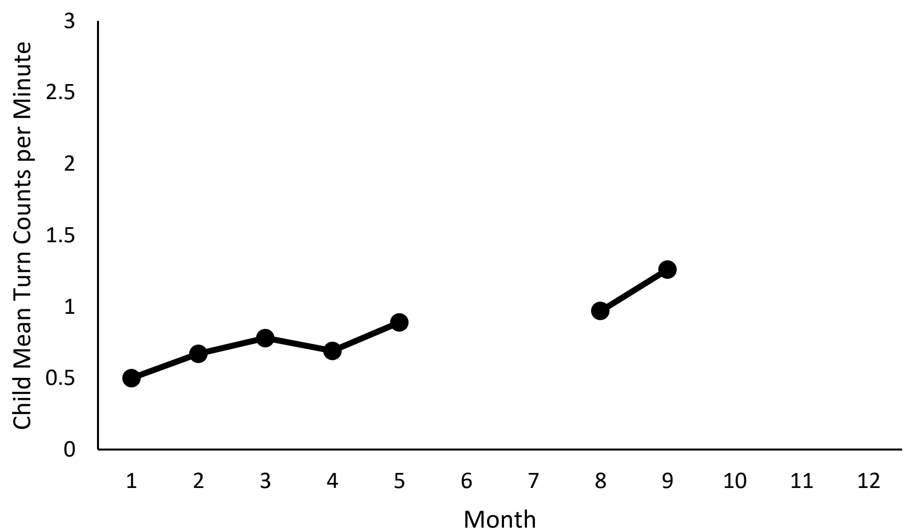

Child Mean Vocalization per Minute
10
9
8
7
6
5
4
3
2
1
0
1 2 3 4 5 6 7 8 9 10 11 12


Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
0
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 16.

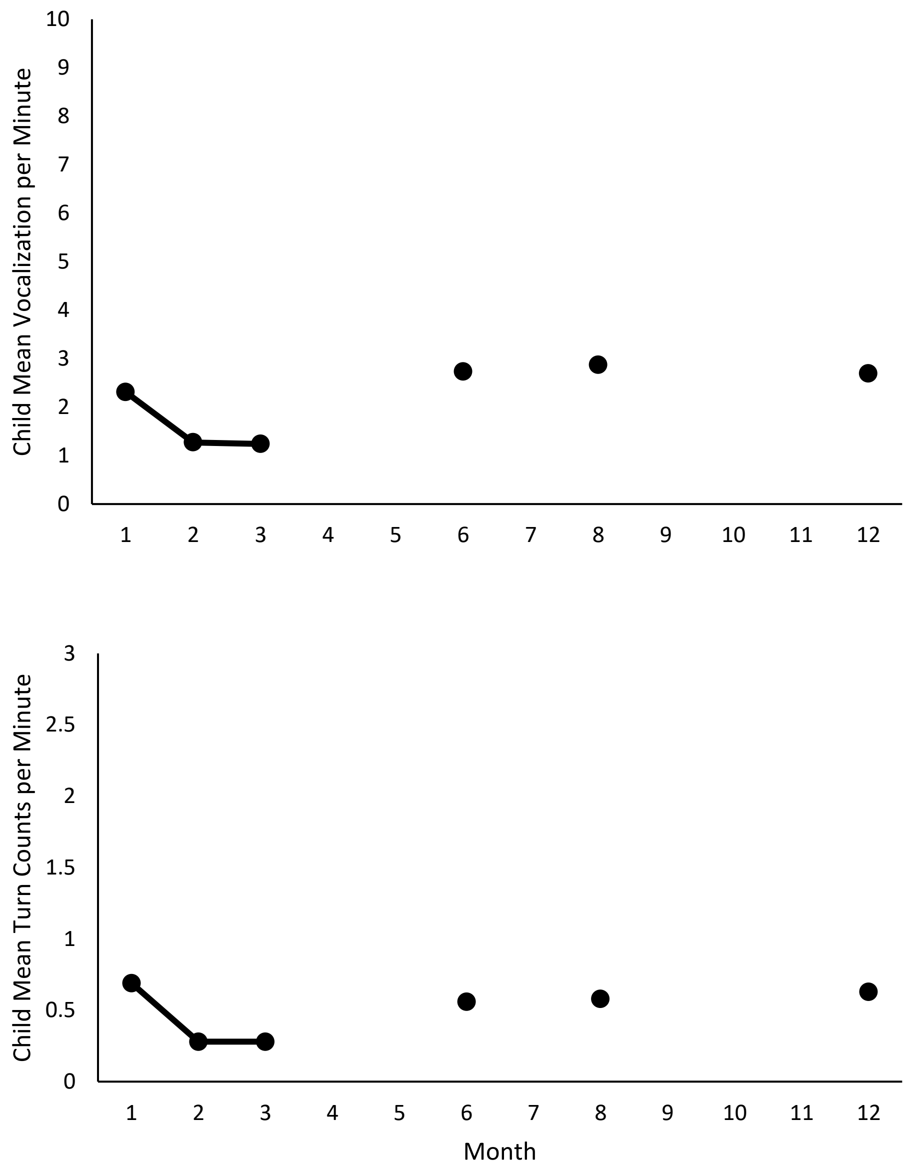


Child Mean Vocalization per Minute
0
1
2
3
4
5
6
7
8
9
10
1 2 3 4 5 6 7 8 9 10 11 12



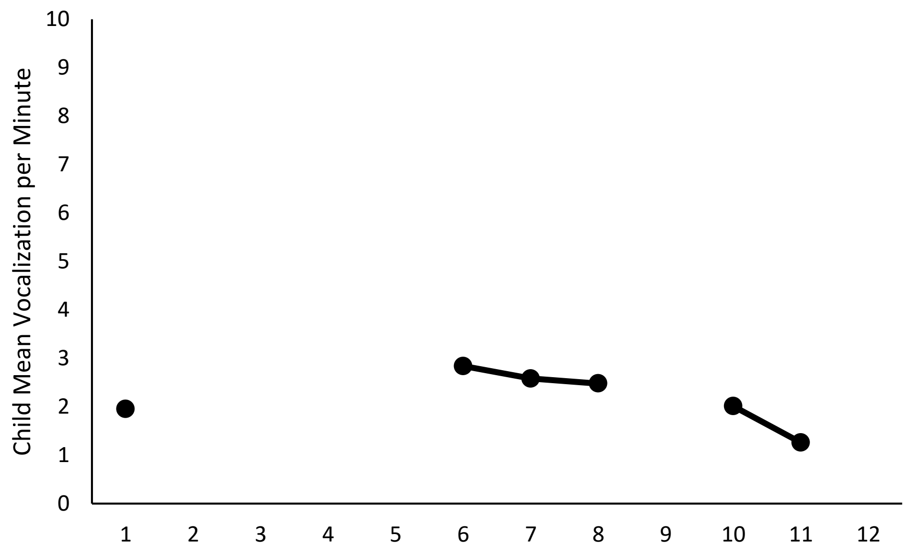
Child Mean Turn Counts per Minute
0
0.5
1
1.5
2
2.5
3
1 2 3 4 5 6 7 8 9 10 11 12
Month

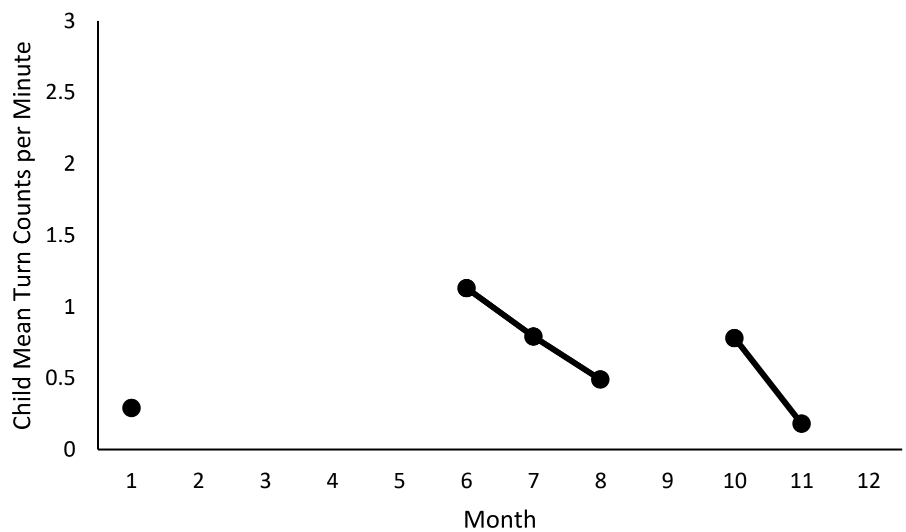
Child 17.



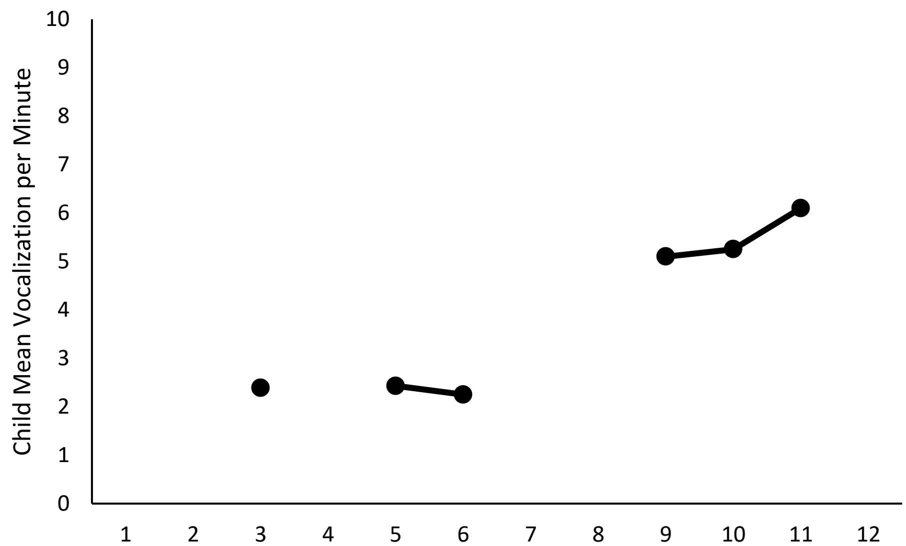
Child Mean Vocalization per Minute
10
9
8
7
6
5
4
3
2
1
0
1 2 3 4 5 6 7 8 9 10 11 12
Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
0
1 2 3 4 5 6 7 8 9 10 11 12
Month

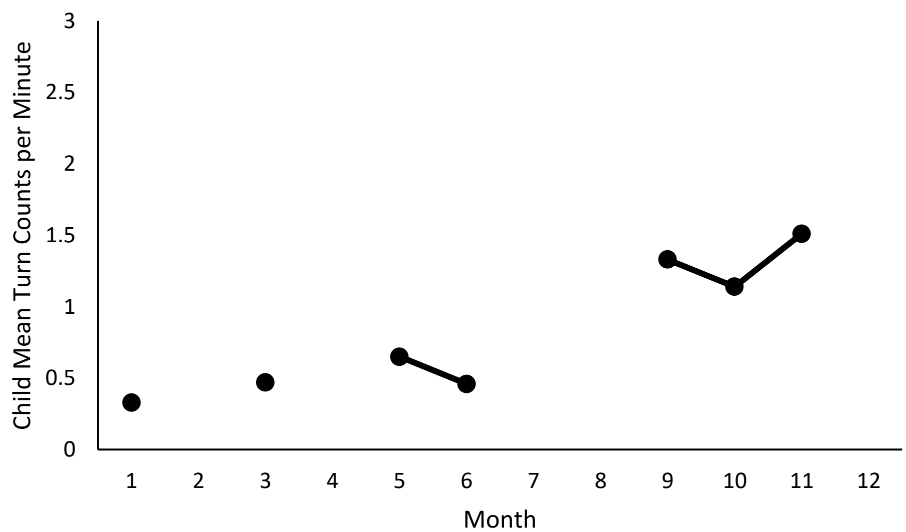
Child 18.


Child Mean Vocalization per Minute
10
9
8
7
6
5
4
3
2
1
0
1
2
3
4
5
6
7
8
9
10
11
12

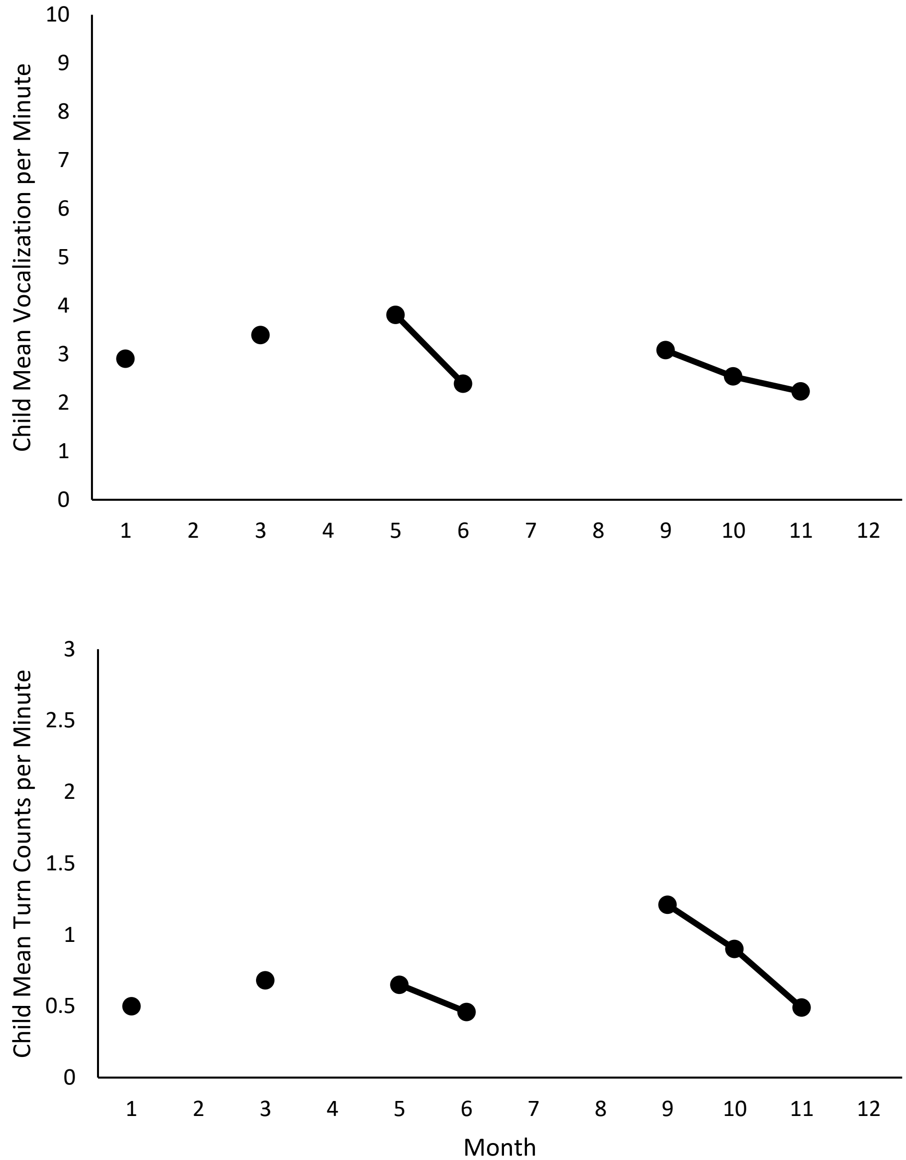

Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
0
1
2
3
4
5
6
7
8
9
10
11
12
Month

Child 19.

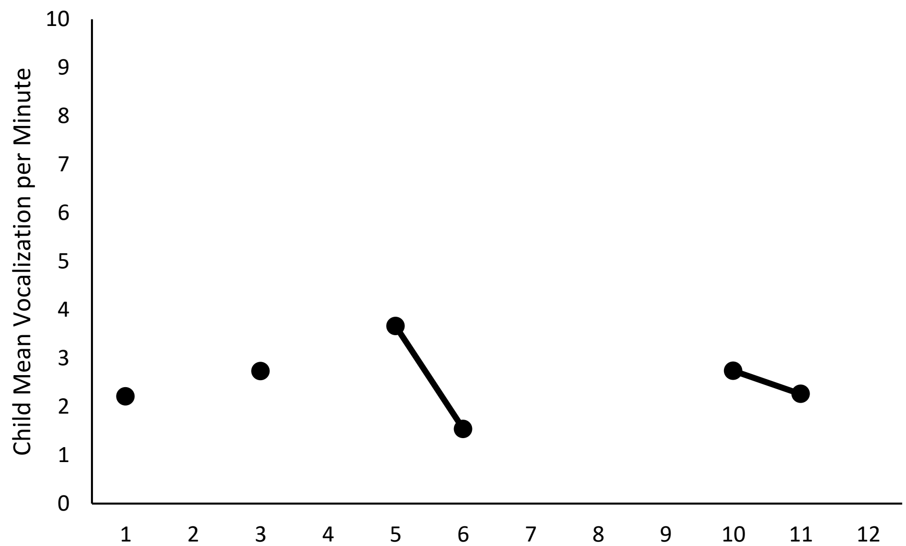

Child Mean Vocalization per Minute
0
1
2
3
4
5
6
7
8
9
10
1 2 3 4 5 6 7 8 9 10 11 12


Child Mean Turn Counts per Minute
0
0.5
1
1.5
2
2.5
3
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 20.


Child Mean Vocalization per Minute
0
1
2
3
4
5
6
7
8
9
10
1
2
3
4
5
6
7
8
9
10
11
12
Child Mean Turn Counts per Minute
0
0.5
1
1.5
2
2.5
3
Month

Child 21.



Child Mean Vocalization per Minute
0
1
2
3
4
5
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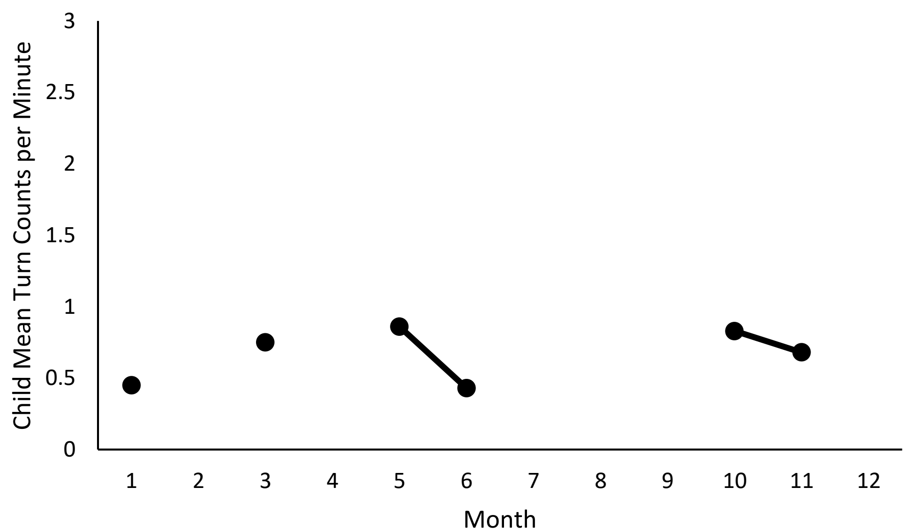
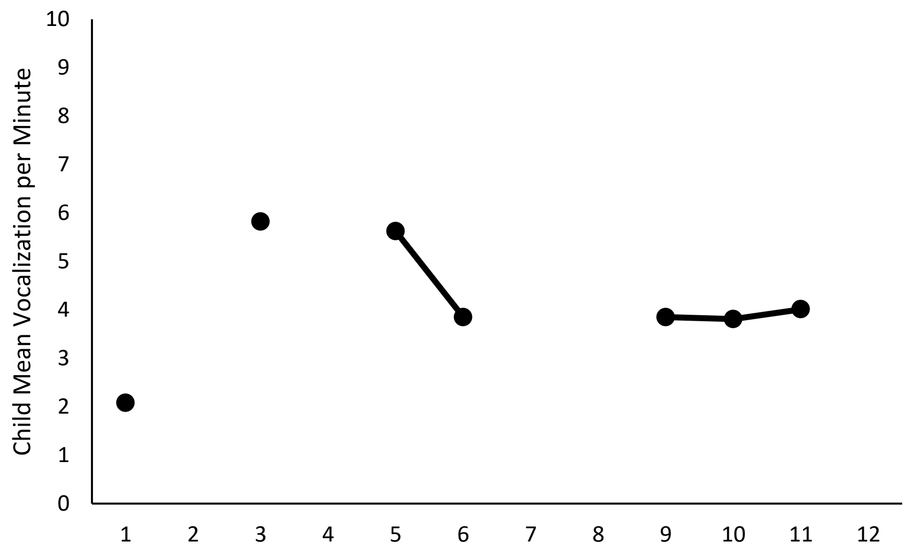
7
8
9
10
1 2 3 4 5 6 7 8 9 10 11 12



Child Mean Turn Counts per Minute
0
0.5
1
1.5
2
2.5
3
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 22.


Child Mean Vocalization per Minute
0
1
2
3
4
5
6
7
8
9
10
1
2
3
4
5
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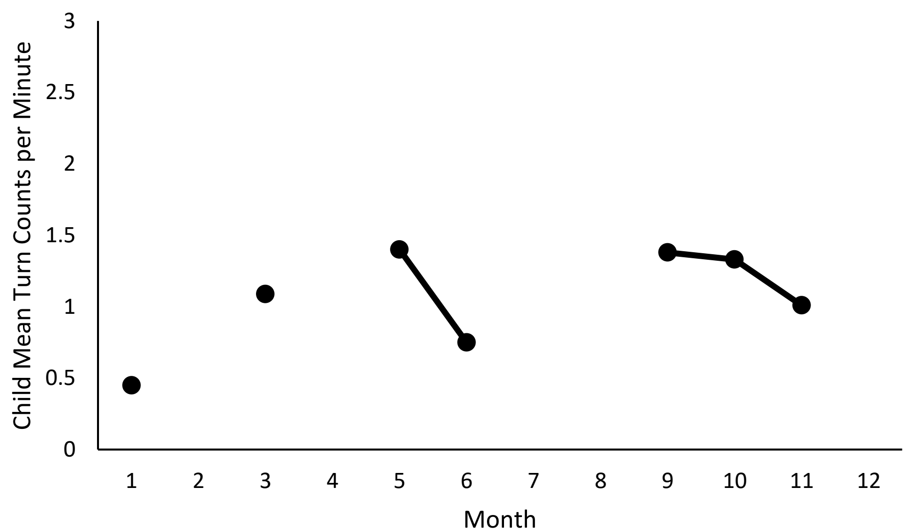
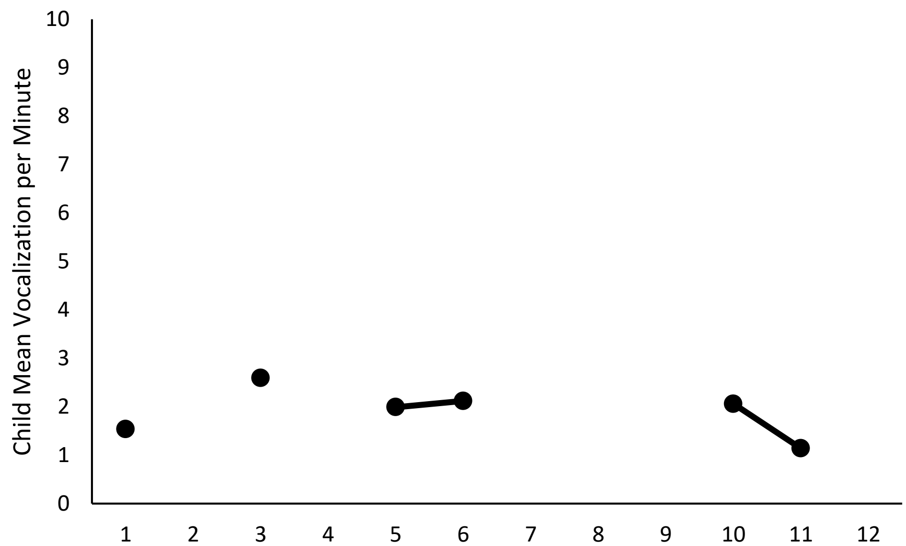
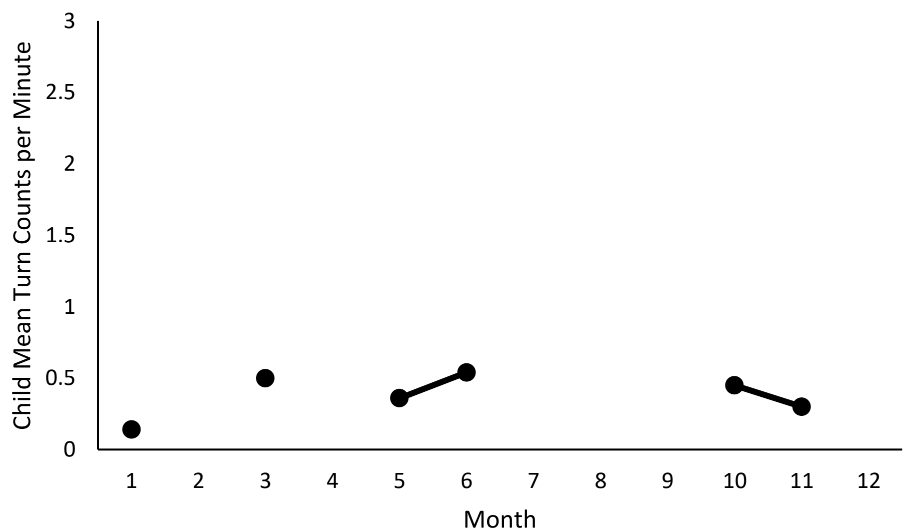
8
9
10
11
12

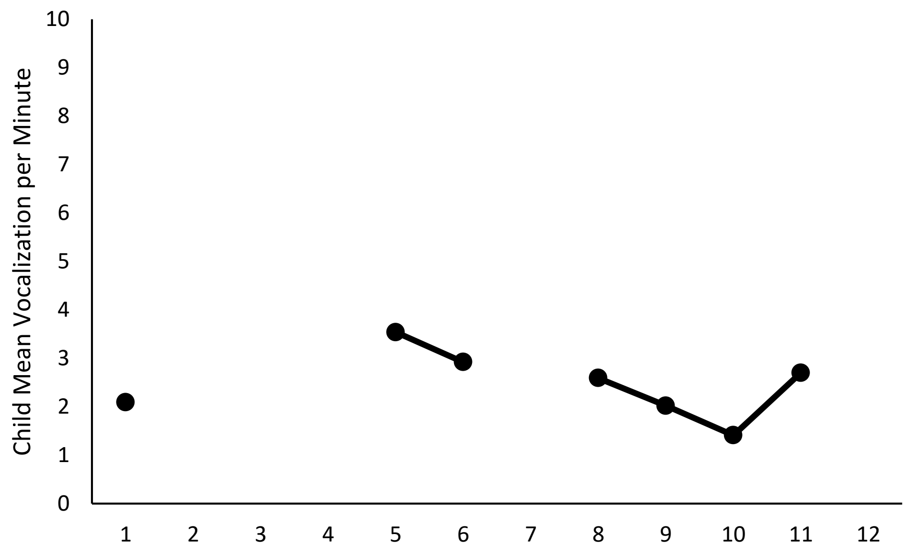

Child Mean Turn Counts per Minute
0
0.5
1
1.5
2
2.5
3
1
2
3
4
5
6
7
8
9
10
11
12
Month

Child 23.

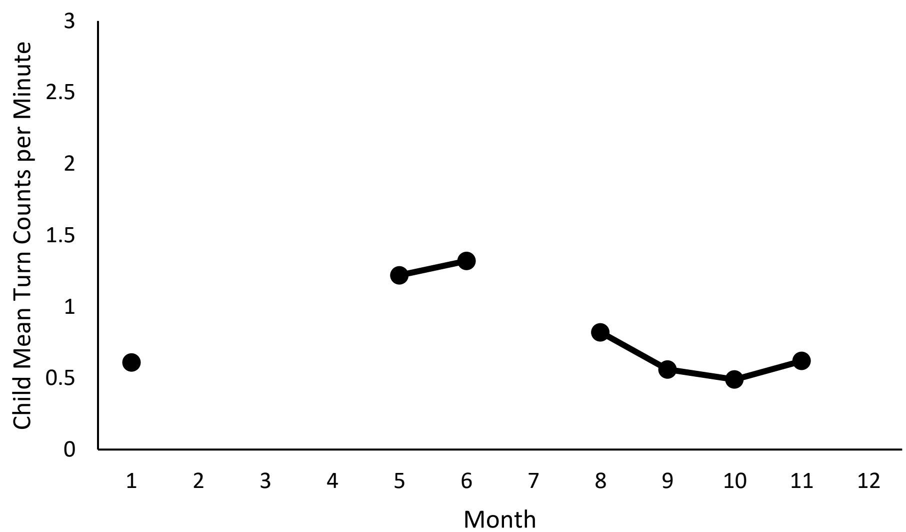

Child Mean Vocalization per Minute
0
1
2
3
4
5
6
7
8
9
10
1 2 3 4 5 6 7 8 9 10 11 12


Child Mean Turn Counts per Minute
0
0.5
1
1.5
2
2.5
3
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 24.

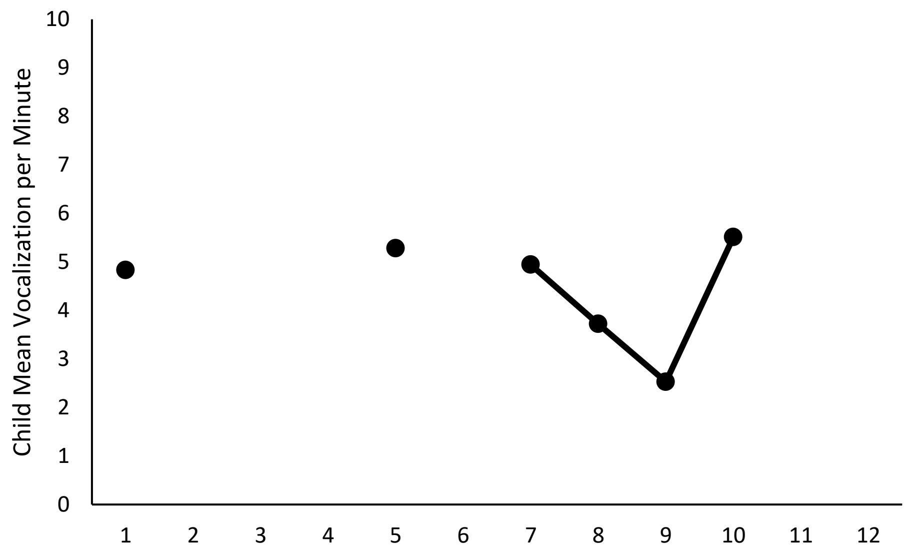


Child Mean Vocalization per Minute
10
9
8
7
6
5
4
3
2
1
0
1 2 3 4 5 6 7 8 9 10 11 12



Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
0
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 25.



Child Mean Vocalization per Minute
10
9
8
7
6
5
4
3
2
1
0
1
2
3
4
5
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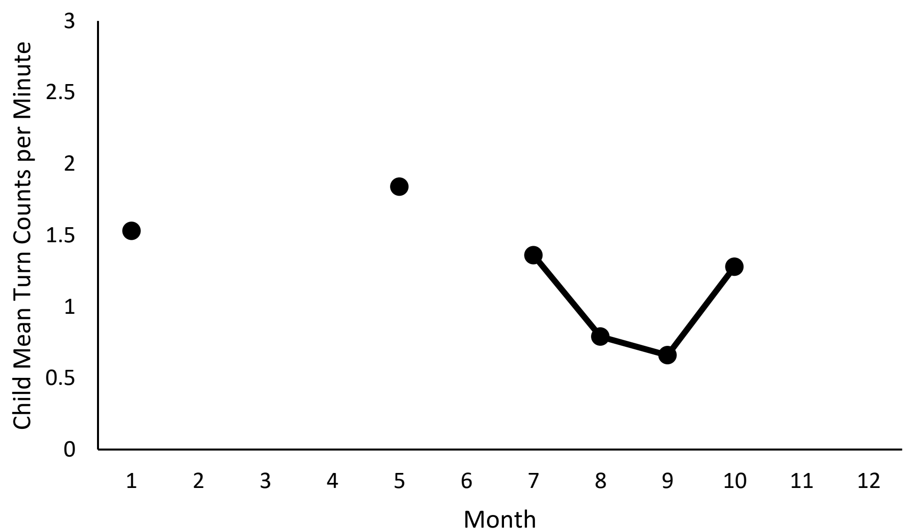
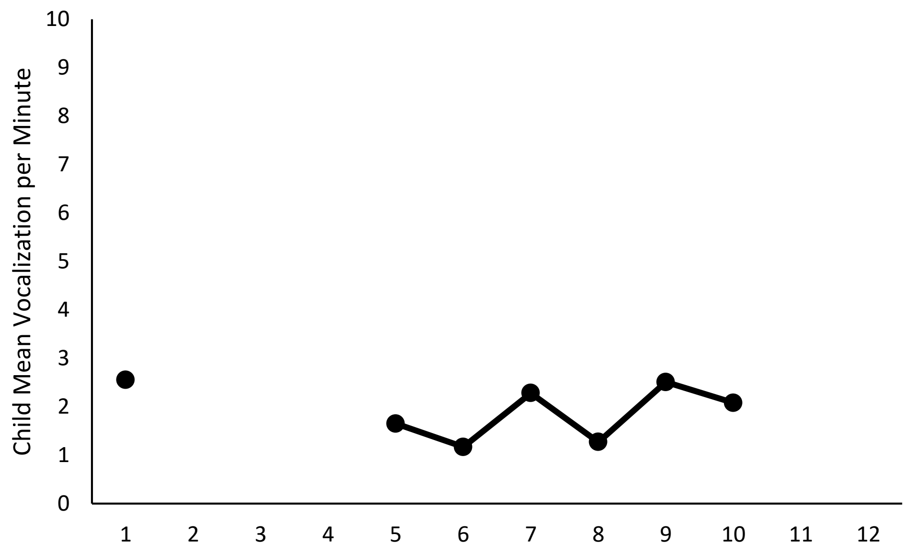
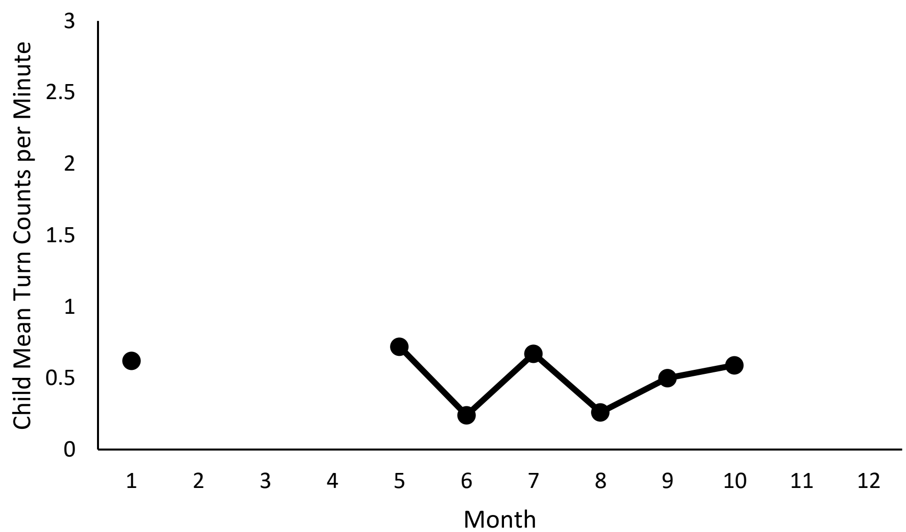
7
8
9
10
11
12



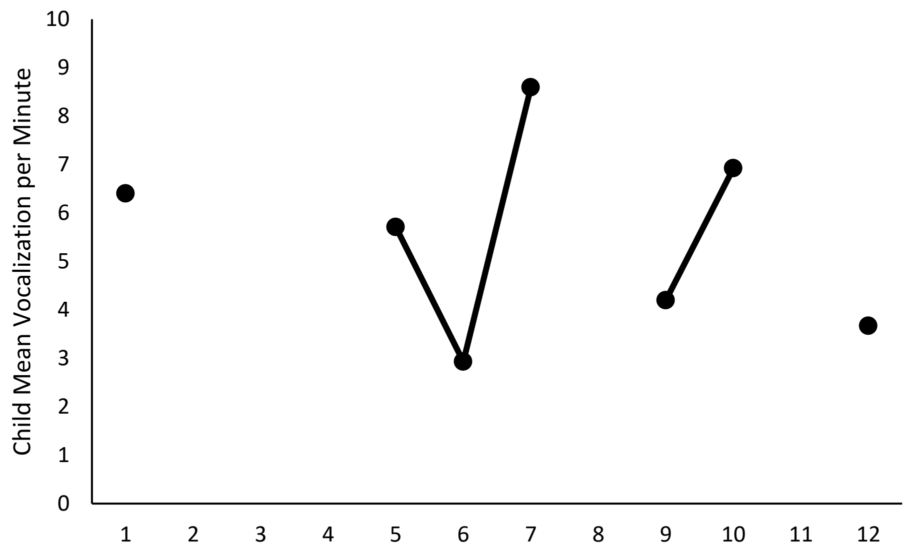
Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
0
1
2
3
4
5
6
7
8
9
10
11
12
Month

Child 26.

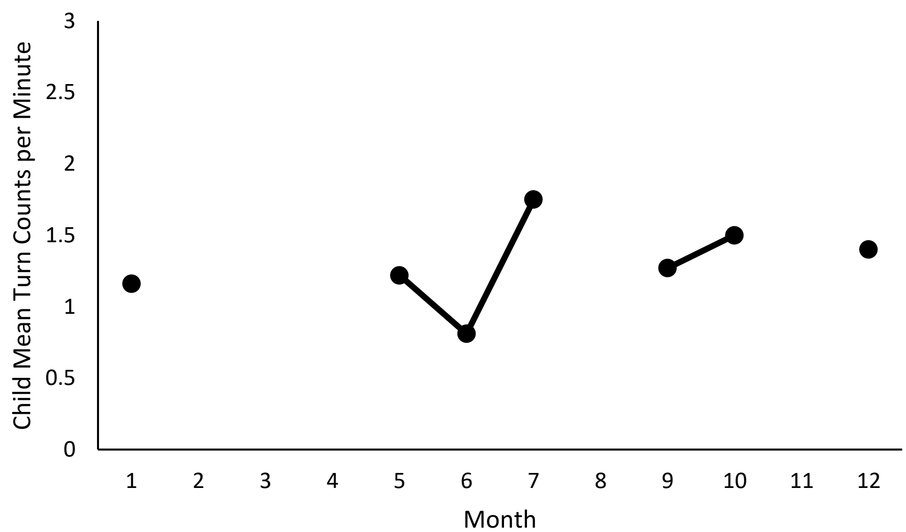

Child Mean Vocalization per Minute
0
1
2
3
4
5
6
7
8
9
10
1 2 3 4 5 6 7 8 9 10 11 12


Child Mean Turn Counts per Minute
0
0.5
1
1.5
2
2.5
3
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 27.

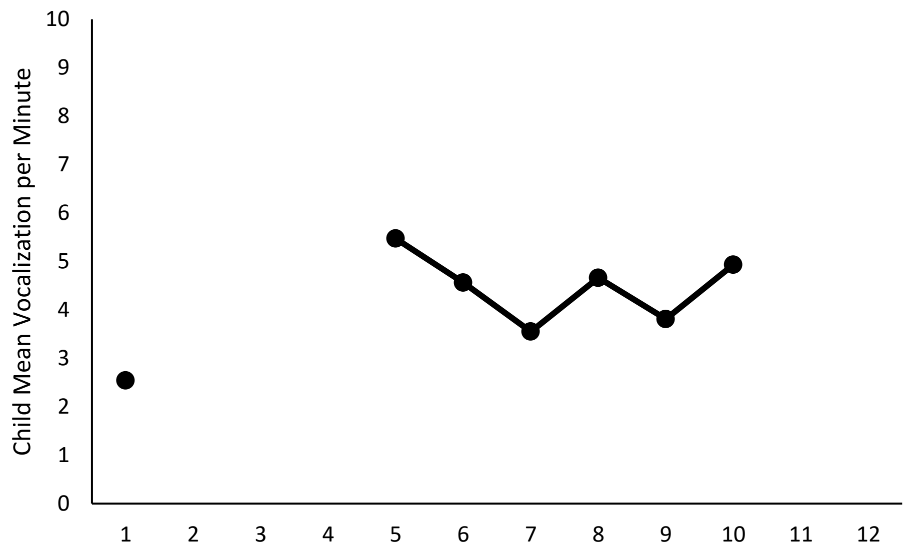


10
9
8
7
6
5
4
3
2
1
0
Child Mean Vocalization per Minute
1 2 3 4 5 6 7 8 9 10 11 12



3
2.5
2
1.5
1
0.5
0
Child Mean Turn Counts per Minute
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 28.


Child Mean Vocalization per Minute
10
9
8
7
6
5
4
3
2
1
0
1
2
3
4
5
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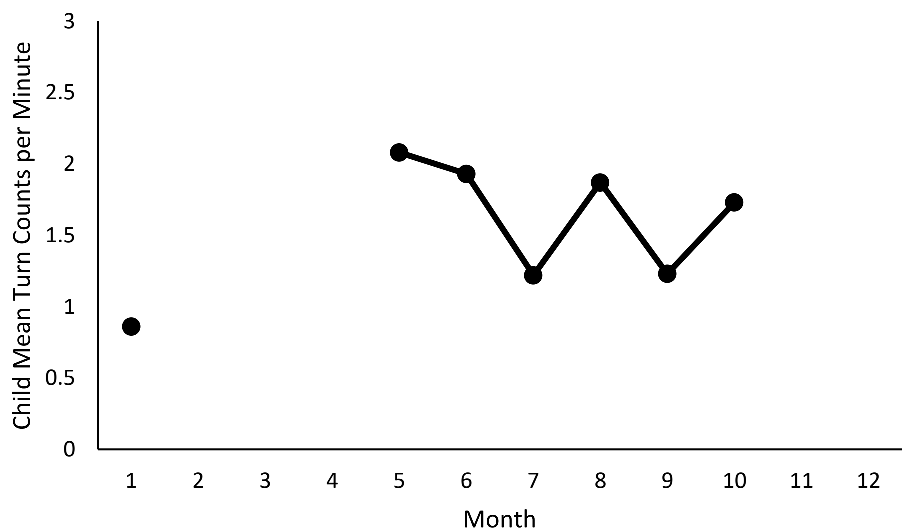
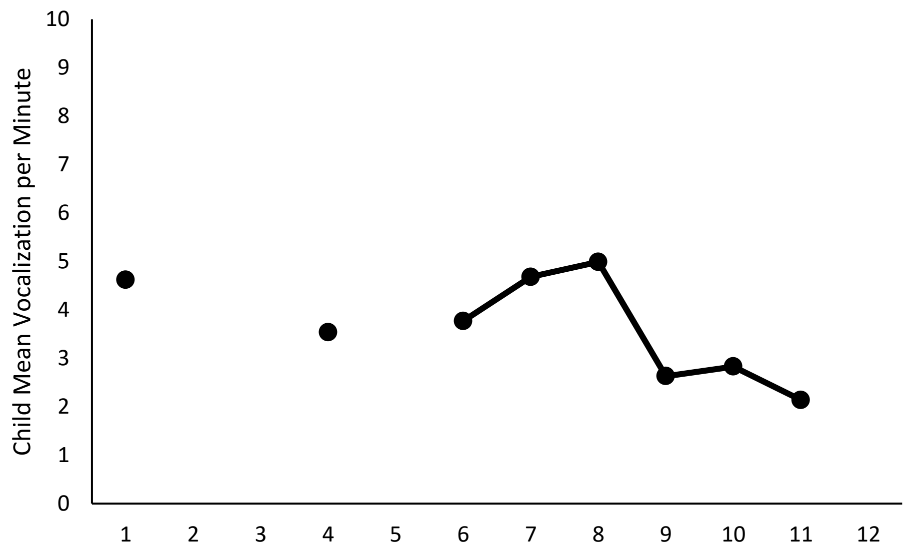
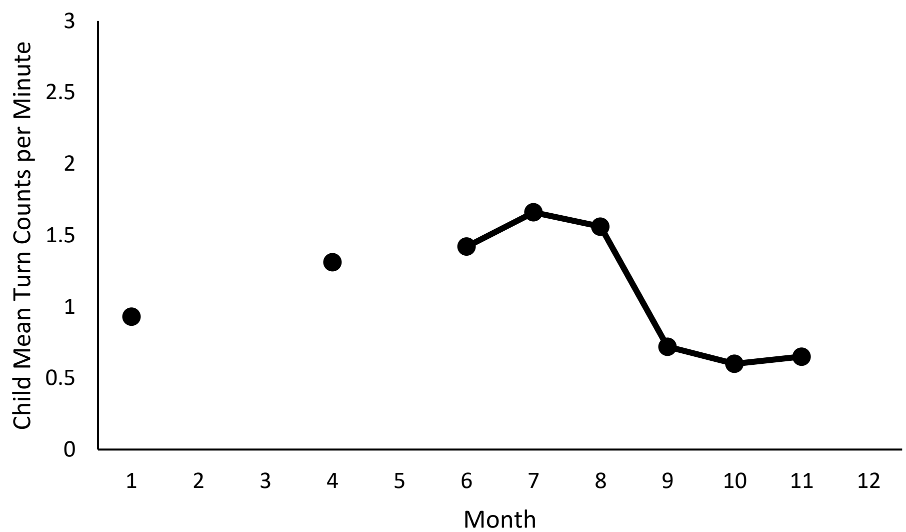
7
8
9
10
11
12


Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
0
1
2
3
4
5
6
7
8
9
10
11
12
Month

Child 29.

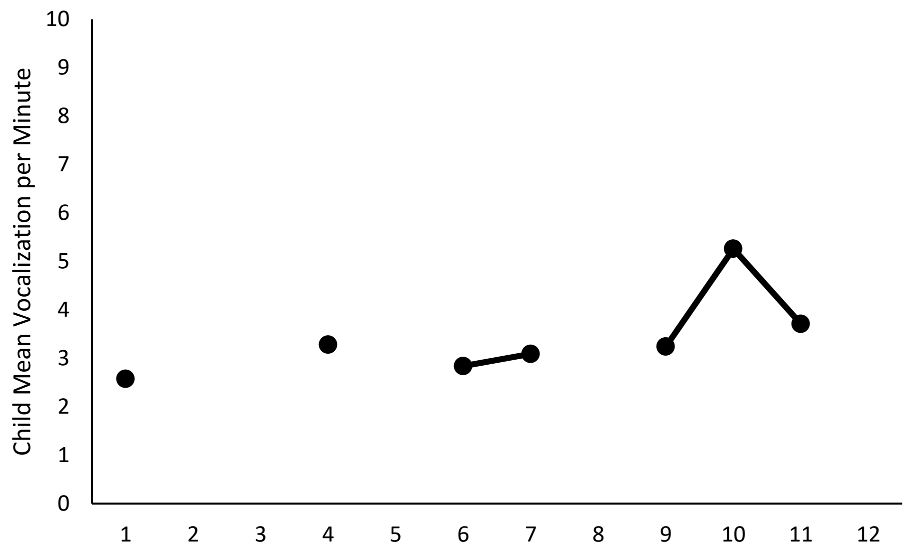


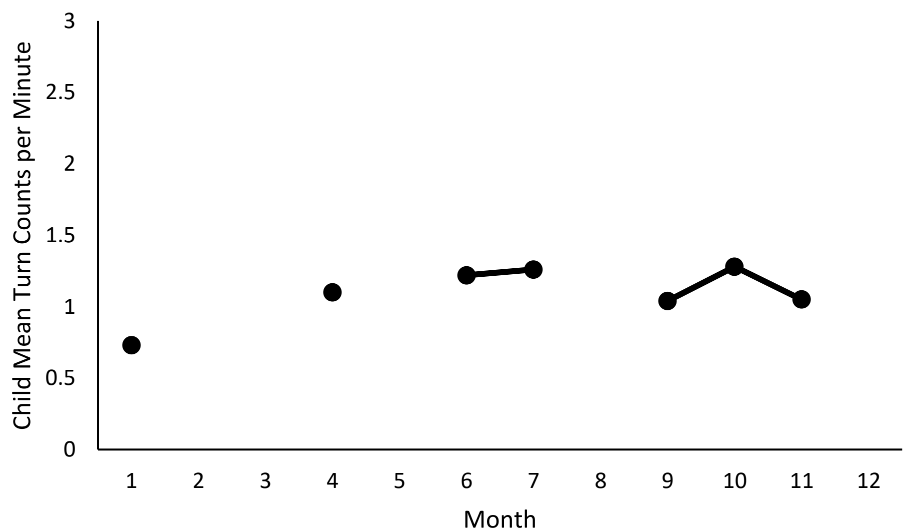
Child Mean Vocalization per Minute
10
9
8
7
6
5
4
3
2
1
0
1 2 3 4 5 6 7 8 9 10 11 12



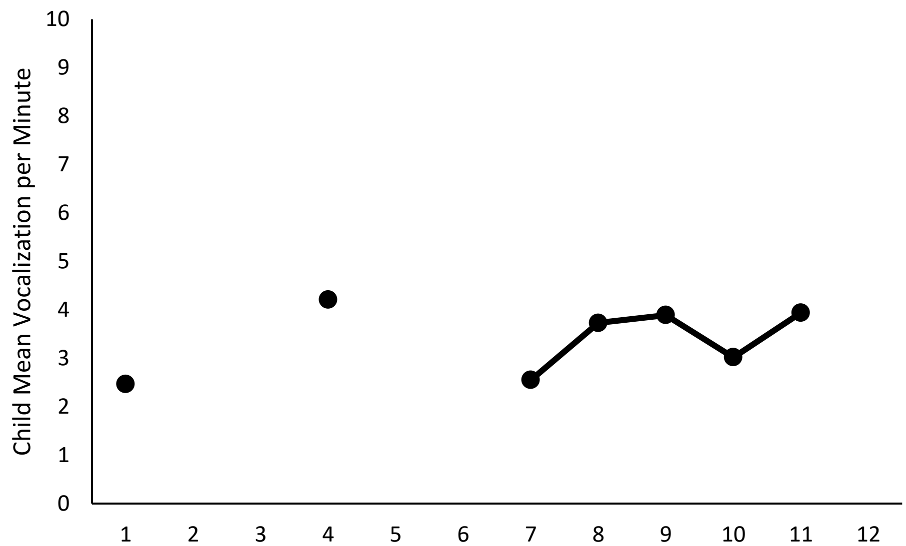
Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
0
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 30.


Child Mean Vocalization per Minute
10
9
8
7
6
5
4
3
2
1
0
1 2 3 4 5 6 7 8 9 10 11 12


Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
0
1 2 3 4 5 6 7 8 9 10 11 12
Month

Child 31.



Child Mean Vocalization per Minute
10
9
8
7
6
5
4
3
2
1
0
1
2
3
4
5
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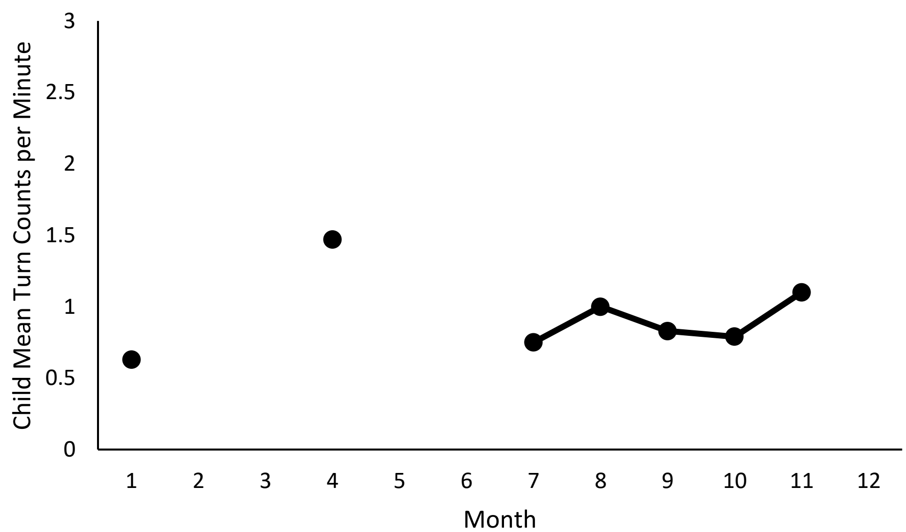
7
8
9
10
11
12



Child Mean Turn Counts per Minute
3
2.5
2
1.5
1
0.5
0
1
2
3
4
5
6
7
8
9
10
11
12
Month