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APPLIED SOFTWARE TOOLS FOR SUPPORTING CHILDREN WITH INTELLECTUAL
DISABILITIES

by

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ABSTRACT

We explored the level of technology utilization in supporting children with cognitive disabilities at schools, speech clinics, and with assistive communication at home. Anecdotal evidence, literature research, and our own survey of special needs educators in Central Florida reveal that use of technology is minimal in classrooms for students with special needs even when scientific research has shown the effectiveness of video modeling in teaching children with special needs new skills and behaviors. Research also shows that speech and language therapists utilize a manual approach to elicit and analyze language samples from children with special needs. While technology is utilized in augmentative and alternative communication, many caregivers utilize paper-based picture exchange systems, storyboards, and daily schedules when assisting their children with their communication needs. We developed and validated three software frameworks to aid language therapists, teachers, and caregivers in supporting children with cognitive disabilities and related special needs. The Analysis of Social Discourse Framework proposes that language therapists use social media discourse instead of direct elicitation of language samples. The framework presents an easy-to-use approach to analyzing language samples based on natural language processing. We validated the framework by analyzing public social discourse from three unrelated sources. The Applied Interventions for eXceptional-needs (AIX) framework allows classroom teachers to implement and track interventions using easy-to-use smartphone applications. We validated the framework by conducting a sixteen-week pilot case study in a school for students with special needs in Central Florida. The Language Enhancements for eXceptional Youth (LEXY) framework allows for the development of a new class of augmentative and alternative communication tools that are based on conversational chatbots that assist children with special needs while utilizing a model of the

world curated by their caregivers. We validated the framework by simulating an interaction between a prototype chatbot that we developed, a child with special needs, and the child's caregiver.

To Asia and Bassel.
For everything you are
&
everything you are not.

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I would like to thank my advisor, Dr. Hughes for allowing my restless mind to wander into the realm of the impossible. I would also like to express my appreciation to Dr. Sims for focusing my methodology, Dr. Wiegand for reminding me that my research is only as important as the questions I ask, and the compassionate Dr. Dieker for opening her office door for me that Fall day, letting me cry on her shoulders, literally and figuratively, and starting me on this path.

I would like to acknowledge the school where we conducted our case study, with special recognition to Ms. Carol Milano and Dr. Kelly Schaffer, for thinking outside the box and believing in my research. Thank you to The Institute for Simulation and Training at UCF for being my home while I pursued four graduate degrees.

On a personal note, I wish to apologize to my father, Zuhair, who passed away before witnessing the completion of this work, I trust you are smiling down on me from heaven; to give special thanks and appreciation to my mother, Hayat, for not allowing the word “quit” to enter our lexicon; my sister, the immaculate Amani, for showing me that everything I can do, she can do better; and my brother, Suhail, for proving to me daily that with enough grit, compassion and selflessness, one person can change the world for the better. No matter the geography, you are always in my heart and on my mind. To my beautiful wife, Ping, for supporting me through endless days, nights, and weekends of never ending work and study, fully knowing there is always more to come.

Last, but certainly not least, to my endless inspiration, my children, Asia and Bassel: I will always aspire to become a fraction of the gift that you are to this world.

TABLE OF CONTENTS

LIST OF FIGURES	x
LIST OF TABLES	xii
CHAPTER ONE: INTRODUCTION.....	1
Fragile X Syndrome	2
Software Frameworks	7
CHAPTER TWO: LITERATURE REVIEW	10
Fragile X Syndrome.....	10
Language Sample Analysis.....	22
Video Modeling	27
Technology in Classrooms for Students with Special Needs.....	30
Conversational Chatbots	33
CHAPTER THREE: ANALYSIS OF SOCIAL DISCOURSE FRAMEWORK.....	35
Overview.....	35
Tokens, Words, Sentences, Stems and Lemmas	36
Complexity and Diversity.....	37
Frequency Distribution	38
Part of Speech tags.....	40
Misspellings	40
Stopwords	41

Results and Discussion	43
CHAPTER FOUR: VIDEO MODELING SURVEY	52
Overview.....	52
Results and Discussion	54
CHAPTER FIVE: THE AIX FRAMEWORK.....	61
Overview.....	61
Results.....	76
CHAPTER SIX: THE LEXY FRAMEWORK.....	78
Overview.....	78
Results.....	88
Simulation of Schedule Board Activity	88
Simulation of Schedule Board Activity	91
Simulation of a Coping Board	92
CHAPTER SEVEN: CONCLUSION AND FUTURE THOUGHTS	98
Analysis of Social Discourse Framework.....	98
Video Modeling Survey	100
The AIX Framework.....	102
The LEXY Framework	103
Tying It All Together.....	104
APPENDIX A: APPROVAL OF HUMAN RESEARCH.....	106

APPENDIX B: FULL LANGUAGE SAMPLE ANALYSIS OF THINK DIFFERENT

POEM 108

REFERENCES118

LIST OF FIGURES

Figure 1: Usage of "Fragile X" in Language.	4
Figure 2: Illustration of relative cognitive performance of the Fragile X phenotype.	5
Figure 3: DNA Strand.	13
Figure 4: A gene is a sequence of pairs in the DNA molecule.....	14
Figure 5: The famous cookie theft image often used to elicit language samples by language therapists.	26
Figure 6 Survey question 1, are you familiar with video modeling?.....	54
Figure 7 Survey question 2, do you use video modeling?	55
Figure 8 Survey question 3, is your process efficient?	56
Figure 9 Survey question 4, what do you like the most about using video modeling?	56
Figure 10 Survey question 5, what do you like the least about using video modeling?.....	57
Figure 11 Survey question 6, are you using other apps?	58
Figure 12 Survey question 7, what do you like most about the apps you use?	58
Figure 13 Survey question 8, what do you like the least about your apps?	59
Figure 14 AIX Architecture. Comprised of four databases, three engines, three front ends and an authorization & authentication layer.	64
Figure 15 Using the app to track behaviors.	71
Figure 16 Visual Model Intervention.	72
Figure 17 A simplified model of a typical chatbot interaction.....	79
Figure 18 The LEXY Framework allows actors to curate the model of the world.	80
Figure 19 A simulated conversation between a prototype chatbot and two actors, the child with autism and their caregiver.	83

Figure 20 General Architecture of the LEXY Framework.	87
Figure 21 The child informing the chatbot that the child wants to watch TV	88
Figure 22 The parent is building the model of the world conversationally.	89
Figure 23 The child repeating the request, after the model of the world has been built.....	89
Figure 24 The child interacting with the chatbot after completing the required chore.....	90
Figure 25 A parent using our prototype software to create a schedule.	91
Figure 26 The prototype chatbot responding to a simulation of a child conversation.....	94
Figure 27 A parent curating a coping board conversationally.....	95
Figure 28 A simulation of a child interacting with the chatbot when needing to cope.....	96
Figure 29 The chatbot handling multiple scenarios at once.	97

LIST OF TABLES

Table 1 Frequency Distribution of Words in the Think Different poem.....	39
Table 2 Frequency Distribution of length of words for the Think Different poem	39
Table 3 Source One: First Public Blog Post Analysis.....	46
Table 4 Source One: Second Public Blog Post Analysis	47
Table 5 Source One: Third Public Blog Post Analysis	47
Table 6 Source One: Fourth Public Blog Post Analysis	48
Table 7 Source Two: First Public Facebook Post Analysis.....	48
Table 8 Source Two: Second Public Facebook Post Analysis	49
Table 9 Source Two: Third Public Facebook Post Analysis	49
Table 10 Source Two: Fourth Public Facebook Post Analysis	50
Table 11 Dissertation Abstract	50
Table 12 Author’s Blog Post.....	51
Table 13 Number of Interfering Behaviors Recorded Per Week	77
Table 14 Daily Average of Recorded Interfering Behaviors.....	77

CHAPTER ONE: INTRODUCTION

This dissertation was born out of the desire to contribute to the well-being of children with cognitive disabilities. This desire led to the following anecdotal observations, which we confirmed with a literature review of published scientific research: a) Children with cognitive disabilities, and related performance and social anxieties are not always evaluated successfully at speech and language clinics; b) Technology interventions, such as video modeling, are not being commonly implemented in classrooms for students with special needs; c) Technology is not being used to track and analyze interventions in classrooms for students with special needs; and d) The emerging conversational assistants technology is not yet being utilized to support children with cognitive disabilities.

The aforementioned observations lead us to the following research questions:

- a) Can natural language processing be used to automate the process of language sample analysis?
- b) Why is video modeling not used in classrooms for students with special needs?
- c) Would teachers for students with special needs use purpose-built mobile apps to track and analyze interventions in their classrooms?
- d) Can Amazon Lex and Amazon Polly be used to model augmentative and assistive communication tools?
- e) Can we use Amazon Lex and Amazon Polly to develop a conversational chatbot for helping children with intellectual disabilities?

To answer those questions, we conducted a literature review of relevant published scientific research; conducted a survey of 44 special needs educators in Central Florida,

developed three software frameworks; validated the software frameworks; and implemented a 16-week pilot case study in a small school for students with special needs in Central Florida.

In the balance of this chapter we provide a short overview of the Fragile X syndrome; which is the leading diagnosed cause of cognitive disabilities and the leading diagnosed genetic cause of autism, followed by a short overview of the work presented in chapters 2, 3 and 4.

In chapter two we provide literature review of the Fragile X syndrome, language sample analysis, video modeling interventions, use of technology in classrooms for students with special needs, and conversational chatbots. In chapters three, five and six we present the three software frameworks that we developed as part of this research, the validation methodology of those frameworks, and the 16-week pilot case study we performed, the results of the pilot case study, the results of validating the analysis of social discourse framework using language samples, and the results of validating the LEXY framework using simulated conversations. In chapter four we present the special needs educators survey we conducted and its results. In chapter seven we discuss the results presented in chapter four and concludes by tying it all together to present directions for future research and recommendations.

Fragile X Syndrome

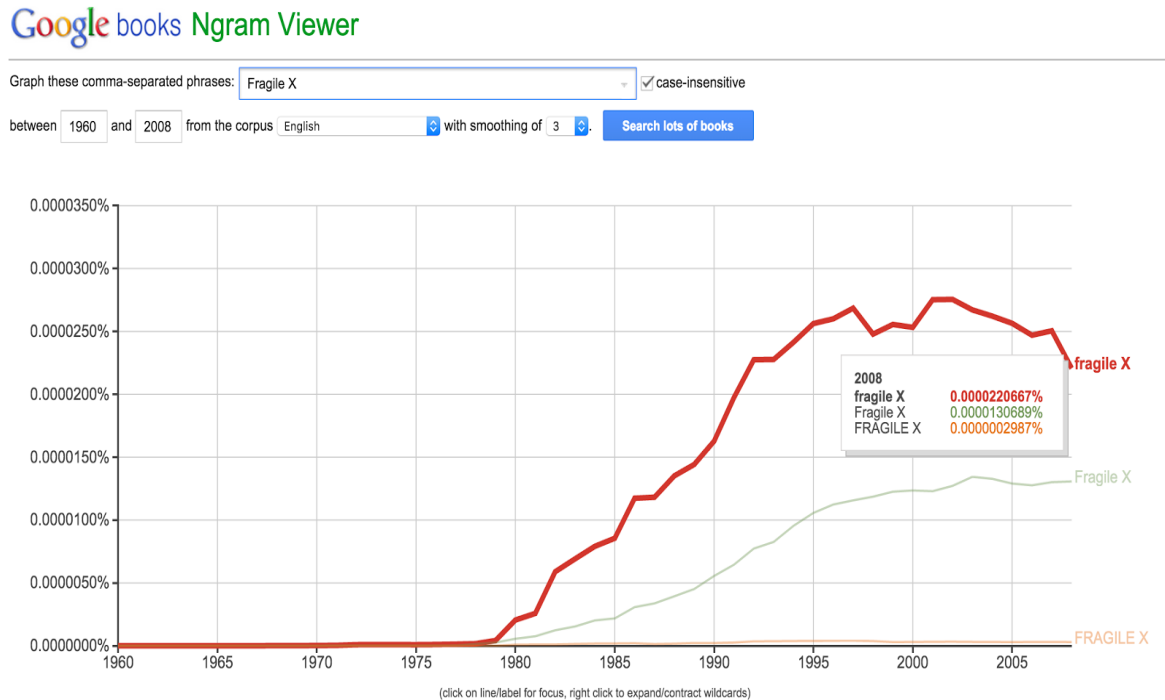
Fragile X is a genetic disorder with no known cure that causes intellectual disabilities, learning disabilities, working memory problems, visual processing problems, anxiety, hyperkinesis, challenging social behaviors, and physical characteristics (Hagerman et al, 2009; Hagerman & Hagerman, 2002; Hagerman, Rivera, & Hagerman, 2008; Hagerman et al, 1996). Fragile X is the leading diagnosed genetic cause of Autism Spectrum Disorder (Wang, Berry-Kravis, & Hagerman, 2010). The CDC declared that we know very little about Fragile X's

natural history, its progression overtime in individuals, and thus we cannot provide effective services to individuals with Fragile X without first characterizing their natural history (CDC, 2014). While research is scant on individuals with Fragile X in their natural environment, the little research conducted shows that children with Fragile X perform below their genetically expected performance and that some of the variance is partially attributed to their home environment (Dyer-Friedman et al., 2002). Research has also shown that Fragile X individuals, males in particular, decline cognitively over time, hitting their peak performance at ages younger than 10 years old (Dyer-Friedman et al., 2002; Wright-Talamante et al., 1996).

Individuals with physical and cognitive disabilities often face obstacles participating in normal life activities. The American Association on Intellectual and Developmental Disabilities defines Intellectual Disability as, “a disability characterized by significant limitations in both **intellectual functioning** and in **adaptive behavior**, which covers many everyday social and practical skills.” (AAIDD, n.d.), emphasis added. Accommodations from employment, to theme parks, to parking spots, to accessibility in software, to buildings’ entrances and ramps, focus on individuals with physical disabilities, a noble cause, yet do not exist for individuals with cognitive disabilities.

Individuals with Fragile X are a subset of the group of people with intellectual disabilities. The Fragile X population confronts compounded challenges in addition to those suffered by the larger population of people with intellectual disabilities. Those extra challenges include physical disabilities, co-morbid autism, hyperkinesia, severe social anxiety, difficulty with abstract thinking, learning disabilities, and other challenges. Additionally, due in part to the relatively recent understanding of Fragile X, much of the efforts in that domain are focused on clinical approaches to treating the syndrome through pharmaceutical drugs. The recency of our

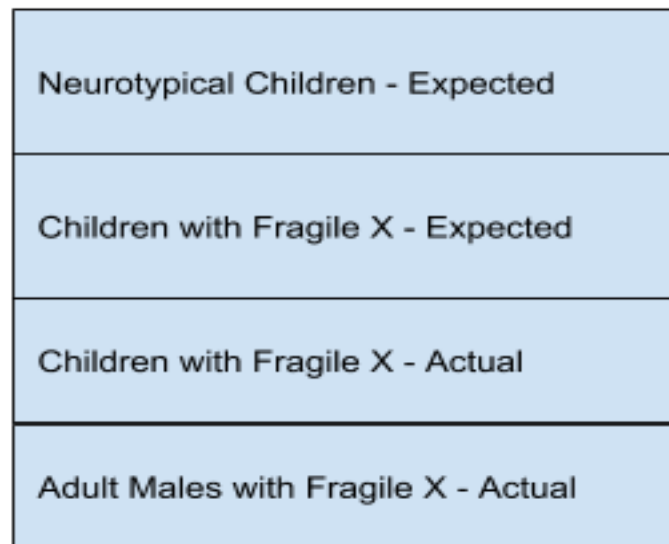
understanding of Fragile X is demonstrated by the frequency of the usage of the term in our written language. Figure 1, illustrates the usage of the term “Fragile X” in language coinciding with the identification and characterization of the syndrome.



Source: Google Books Ngram Viewer
https://books.google.com/ngrams/graph?content=Fragile+X&case_insensitive=on&year_start=1960&year_end=2008&corpus=15&smoothing=3
 Figure 1: Usage of "Fragile X" in Language.

In this dissertation, we advocate for a life participation approach to Fragile X that goes beyond the clinical efforts and extends to interventions, support, and accommodations in real life, at home, school, clinics, and work. One of our goals is to gain a better understanding of how individuals with Fragile X can fully participate in life through the society’s embracing a life participation approach to Fragile X. In order to improve the quality of life for people with Fragile X, including their employment prospects, it is imperative to enable them to perform at their

highest potential, including teaching them basic reading and literacy. Dyer-Friedman et al. (2002) performed a significant study to better understand variations in the cognitive phenotype of individuals with Fragile X. In this study, the researchers performed multiple regression analysis and concluded that aspects of home environment “were associated with overall cognitive development, verbal skills, and attention skills in both the males and females with fragile X” (Dyer-Friedman et al., 2002). In addition, the study showed that school services have no effect on variations in cognitive development and cognitive performance. It is critical to note that Dyer-Friedman et al. (2002), Wright-Talamante (1996), Fisch et al. (1996), and others have all shown that age correlated with the IQ in males with Fragile X. However, this association is negative in that IQ of males with Fragile X declines over time.



Source: image by author

Figure 2: Illustration of relative cognitive performance of the Fragile X phenotype.

Figure 2, not to scale, for illustration purposes only, shows the relative cognitive performance of the Fragile X phenotype, with the Adult Males having the lowest cognitive

performance, and neurotypical children having the highest relative performance. The figure only serves to illustrate the relative cognitive performance of the four groups in the figure. The expected cognitive performance of neurotypical children is based on the parents' mean Full Scale IQ. Since IQ is known to be hereditary this is a good measure of the expected cognitive performance and corresponds to findings of unaffected siblings in the Dyer-Friedman study. The expected Children with Fragile X performance is based on measured IQ of the affected Fragile X children. Basically it is the expected performance based on the biological impact of Fragile X. The actual Children with Fragile X performance is based on the overall cognitive performance (Wechsler, 1949), verbal, performance organization, and processing speed skills of Fragile X children. According to Dyer-Friedman, et al. (2002), this difference between the expected and actual Fragile X performance is partially due to aspects of the home environment. The less supportive and less learning-enriched home environment lead to lower the cognitive performance. The last entry in the figure is the male adult with Fragile X. It is not clear why males with Fragile X regress below their cognitive ability at childhood. Based on the principles of experience dependent neuroplasticity, we suspect, without support of any research evidence, that as males grow older they receive less support and less cognitive stimulation leading to regression in cognitive performance.

There are no known treatments for Fragile X. Currently all efforts for “treating” Fragile X are focused on changing the biology to move the Expected Fragile X Performance closer to the Expected Normal Performance. In contrast, in this dissertation we are focused on improving support for children with Fragile X in the hope that their Actual Fragile X performance moves closer to the Expected Fragile X Performance, congruent with the Dyer-Friedman, et al. (2002) research that found that the home environment was a contributing factor to that gap between the

Actual and Expected performances of children with Fragile X. In other words, our goal is not to change biology but to provide tools that can aid teachers, therapists, parents, and caregivers in supporting children with Fragile X, possibly helping close the gap between their expected and their actual cognitive performances. Any steps that we can take to democratize access to supportive tools, via building easy-to-use, easy-to-attain, tools, will help provide support for caregivers and teachers of children with Fragile X across a broad spectrum of demographics and socio-economic classes. While the motivation for this work is driven primarily by the author's personal experience with Fragile X, the tools developed in this dissertation are not specific to, nor limited to, children with Fragile X, but are applicable to a wide range of cognitive and behavioral challenges regardless of the genetic cause of the challenges.

Software Frameworks

The efforts presented in this research focused on the development of three software frameworks. The Analysis of Social Discourse Framework (ASDF) was developed to aid language and speech therapists in conducting language sample analysis for children with cognitive disabilities and social anxiety. The impetus to developing this framework was the author's observations that children attending speech clinics at the local university were not responding well to graduate students attempting to evaluate the children's language skills due to the children's cognitive disabilities as well as their social and performance anxieties. Without proper evaluation of the child's language, the proper treatment plan could not be curated. As such, the research question at hand is: Can we use natural language processing software to automate the process of analyzing language samples? If the answer is affirmative, then a concluding recommendation would be for language therapists to analyze language samples that

children produce independently, possibly through social media discourse, in lieu of direct elicitation of language samples. We developed an easy-to-use framework for analyzing language samples using natural language processing and validated that it can be used to analyze language samples by analyzing a sampling of public discourse.

While technology continues to evolve at a rapid pace, including at schools, a simple visit to special education classrooms quickly reveals that teachers are not using technology to specifically target interventions for children with special needs. Video modeling is one technology-based approach to interventions that has been studied in literature and shown to be effective in teaching children with special needs new skills, and teaching them how to reduce interfering behaviors. To understand the level of use of video modeling in classrooms for students with special needs we anonymously surveyed 44 special education teachers in Central Florida to better understand their usage of video modeling. The results overwhelming showed that most teachers surveyed do not use video modeling as an intervention, but that they would use video modeling, or other effective technology-based interventions, if provided with easy-to-use, easy-to-attain tools. We developed the Applied Interventions for eXceptional-needs (AIX) framework to aid teachers for students with special needs administer and track interventions in their classrooms. We conducted a 16-week pilot study in a small private school in Central Florida. The study, and post study interviews, showed that once afforded a simple, effective, easy-to-use and easy-to-attain, smartphone-based, software tool, the teacher eagerly used technology to administer and track interventions in her classroom.

Augmentative and alternative communication systems, including the picture exchange communication system, storyboards and picture schedules, have been used for several decades in aiding the communication needs of individuals with special needs. With the very nascent, but

rapid, advent of conversational, voice, artificial intelligence based, assistant devices, such as Amazon Alexa and Google Assistant, we sought to research whether augmentative and alternative communication tools can be modeled using the Amazon Lex and Amazon Polly technologies that underlie the Amazon Alexa voice assistant. We developed LEXY, a framework built on top of Amazon Lex and Amazon Polly that models paper-based augmentative and alternative communication tools. LEXY is novel in that it is the first published conversational framework, of which we are aware, that incorporates multi-actor interactions with one or more of the actors, conversationally curating the model of the world presented to the user with special needs. We simulated human interaction with a prototype chatbot based on the LEXY framework and showed that the LEXY framework can successfully model three common communication tools used with individuals with intellectual disabilities: First/Then storyboards, schedule boards, and coping boards, while successfully allowing a caregiver to conversationally curate the model of the world.

CHAPTER TWO: LITERATURE REVIEW

Fragile X Syndrome

Fragile X is a genetic condition that causes intellectual and learning disabilities, behavioral challenges, autism, and various physical characteristics affecting as many as 1 in every 3600 males and 1 in every 5000 females (NFXF, 2014; Wang, Berry-Kravis, & Hagerman, 2010; Hagerman & Hagerman, 2002). In addition to the main feature of intellectual disabilities, people afflicted with Fragile X often present with clinical symptoms that overlap with various frequently occurring psychiatric and developmental disorders, especially autism, ADHD, speech and language disorders, anxiety disorders and seizures (Hagerman, 2009; Berry-Kravis, et al., 2013).

Fragile X-associated tremor/ataxia syndrome, a Fragile X related disorder discovered only in 2001, is a late onset disorder affecting as many as one in 3000 men over fifty years old and one in 1300 women over fifty. It is characterized by problems with cognition, movement ability and tremors (FXTAS, n.d.). The Fragile X-associated primary ovarian insufficiency (FXPOI) is another Fragile X related disorder. Approximately 20% of female Fragile X carriers will develop FXPOI (Ennis, Ward, & Murray, 2006) characterized by infertility and irregularities in menstrual cycle. As the Fragile X gene was only isolated in 1991, with even more recent discoveries of related disorders, we face a severe lack of understanding of the characterization of natural history of affected individuals and their caregivers.

Individuals afflicted with Fragile X suffer severe intellectual disabilities, learning disabilities, seizures, working memory problems, visual processing problems, vision problems, comorbid autism, sensory processing disorders as well as a host of abnormal physical

characteristics (Hagerman et al., 1996; Hagerman & Hagerman, 2002; Hagerman, Rivera, & Hagerman, 2008). Fragile X is the leading diagnosed genetic cause of Autism Spectrum Disorder (Wang, Berry-Kravis, & Hagerman, 2010) and the most common cause of inherited mental retardation (Hernandez et al., 2009)

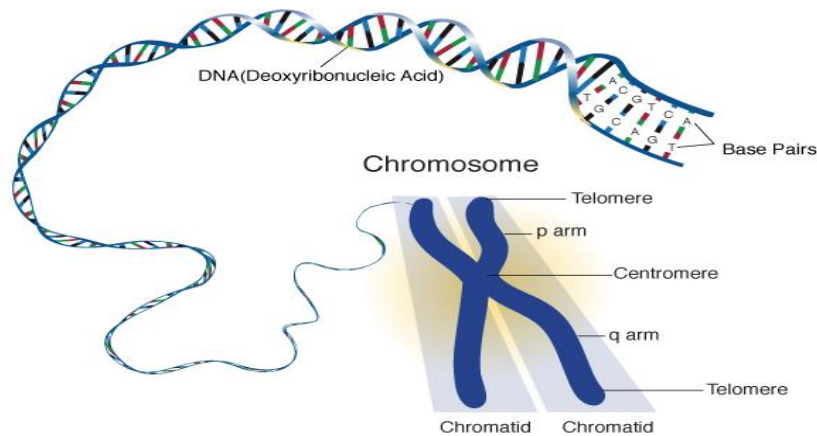
Due to their cognitive disabilities, the majority of males affected with Fragile X cannot attain even the simplest levels of literacy. Males with Fragile X cannot typically recognize letters, decode words, or understand the concept of numbers let alone mathematics. Both males and females suffering Fragile X cannot handle abstract concepts such as time and money, and tend to interpret everything literally (Hagerman & Hagerman, 2002; Hagerman et al., 1996).

Fragile X diagnosis usually comes as a shock to parents if the child is the first of the offsprings to be affected. Often parents and caregivers attribute missing, or late developmental milestones, to natural variances or suspect other factors such as obstructions during delivery or even lead or mercury poisoning. As such, it is common to hear parents describe how their children were not diagnosed until their teenage years or that they discover that much older relatives were diagnosed with Fragile X once a young family member was diagnosed and the genetic counselors helped the family connect the dots.

The National Fragile X Foundation explains testing and diagnostic procedures for Fragile X (NFXF, n.d.). Prior to identifying the Fragile X Mental Retardation Gene (FMR1) the only way to diagnose Fragile X was the not-always-accurate chromosome cytogenetic test. After identifying the FMR1 gene in the 1990s, the “FMR1 DNA Test”, aka “Fragile X DNA Test” was developed to replace chromosome testing. With an accuracy of 99%, the new DNA test became the standard testing procedure for Fragile X. (NFXF, n.d.). The National Fragile X Foundation recommends DNA testing for people that present clinical symptoms suggesting Fragile X,

FXTAS or FXPOI, people with familial history of Fragile X syndrome or cognitive disabilities or autism and people with familial history of carrying the Fragile X gene. Currently there are two different lab procedures for conducting the FMR1 DNA test, the southern blot test and the polymerase chain reaction (PCR) analysis test. The latter has not been as popular in labs due to technical reasons but is quite accurate, quicker and less expensive than the southern blot test. As such, it is likely that once technical hurdles have been crossed, it will become the only test used in the future (NFXF, n.d.). The cost of the tests had been a hurdle in the past, with some labs charging several thousand dollars for testing. Insurance coverage was also spotty and not always available to everybody; this remains the case in many countries outside the USA. In the USA, the cost of the tests has dropped to the \$300-\$600 range, and insurance coverage is more prevalent. The test is usually ordered by a physician or a genetic counselor. The test usually takes 2-4 weeks for results to come back; the results are often a range, such as 200-400, that explains the number of CGG repeats in the X chromosome. In females, the test results typically return two numbers, one for each X chromosome. In males, the test results typically return one number, although some males, termed mosaics, have multiple sets of CGG expansions in their single X chromosome.

According to the National Institute of Health (NIH, 2014), Deoxyribonucleic acid (DNA) holds the blueprint for how living organisms are built. A biomolecule, DNA, is made of two long twisted strands containing complementary genetic information. Figure 3 illustrates a DNA strand. A segment of the DNA that is transferred from parents to offsprings is known as a gene, it confers genetic traits to the offsprings. A gene is organized into chromosomes. Humans have 23 pairs of chromosomes. Each pair has one chromosome from the mother and another chromosome from the father (NIH, 2014).

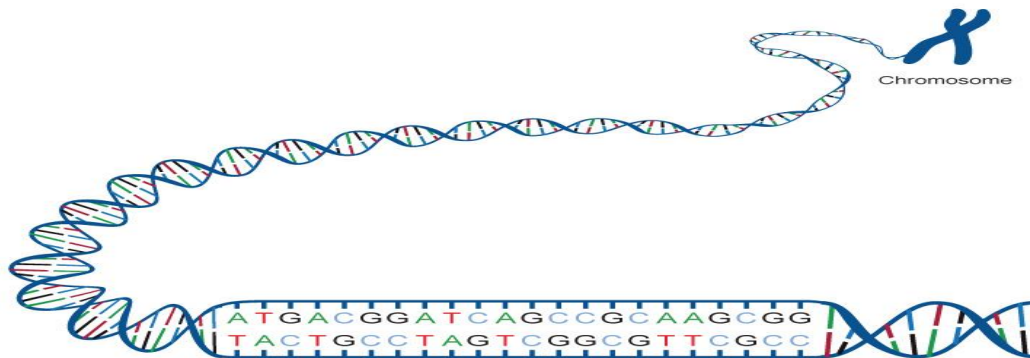


Source: The National Human Genome Research Institute's Talking Glossary
<http://www.genome.gov/glossary/>.
 Figure 3: DNA Strand.

Of the 23 pairs of chromosomes, 22 are numbered chromosomes called autosomes. The 23rd pair is the sex chromosome and is made up of the Y chromosome and the X chromosome. A human female has two X chromosome in the 23rd pair. A human male's sex chromosomes are one X chromosome and one Y chromosome. A human offspring always gets one X chromosome from its mother. If the father passed his X chromosome to the offspring the offspring would be a female with two X chromosomes; one from each parent. If the father passes his Y chromosome, the offspring would be a male, having the father's Y chromosome and one of the mother's X chromosomes. Fragile X is a genetic mutation in the X chromosome that causes it to look brittle under a microscope, hence the term Fragile X. It can only be passed to male children from their mother. Daughters can receive Fragile X from their mothers or can become carriers if their father is a carrier, as will be further explained later.

The DNA molecule is made up of four types of bases, ACGT: Adenine, Cytosine, Guanine, Thymine. Adenine pairs with Thymine and Cytosine pairs with Guanine as shown in

Figure 4 (NIH, 2014). A sequence of pairs in the DNA molecule is called a gene and it carries the instructions to assemble a protein.



Source: The National Human Genome Research Institute's Talking Glossary
<http://www.genome.gov/glossary/>.

Figure 4: A gene is a sequence of pairs in the DNA molecule

The Fragile X Mental Retardation 1 (FMR1) gene contains CGG segments. In a typical person, those segments repeat 5 to 40 times. People with a premutation, aka carriers, have an expansion of the CGG with a repetition range of 55 to 200. In female carriers, the repetition expands to higher than 200 CGG in cells that develop to eggs. Thus premutation (carrier) mothers pass the full mutation to their children resulting in a full mutation Fragile X Syndrome. The premutation in men does not expand above 200. Thus, their daughters would also be carriers who have the premutation but not the full mutation disorder; they will be carriers of the syndrome instead. A carrier father would have unaffected sons and carrier daughters. A full mutation mother would have full mutation Fragile X daughters and sons. A full mutation father would have unaffected sons and full mutation Fragile X daughters. Full mutation Fragile X males are extremely low functioning and are extremely unlikely to have children. Studies have

shown that some carriers end up with related disorders later in life such as the FragileX-associated Tremor/Ataxia Syndrome (FXTAS) and the FragileX-associated Primary Ovarian Insufficiency (FXPOI). Men only pass the Y chromosome to their sons, so the sons are not affected (from their father's side) as the Y chromosome does not contain the FMR1 gene (NIH, 2014b; Hagerman & Hagerman, 2002; Hagerman, 2008; O'keefe, 2014).

The FMR1 gene is important because it contains instructions for making the Fragile X Mental Retardation Protein (FMRP). The FMRP regulates the production of other proteins and plays an important role in the development of synapses (NIH, 2014b), which are specialized connections between neurons. Thus, the disorder has a devastating effect on brain functionality, cognition, memory, and the nervous system. The abnormal expansion of the CGG repeats silences the FMR1 gene which results in no, or reduced, production of the FMRP protein. Females have two X chromosomes. Since they only get the full mutation from their mothers they will always have one normal X chromosome, unless their father is also a carrier, in which case they will get a premutation X chromosome from the father. In either case, the FMR1 gene is not completely silenced and thus they still have some level, albeit reduced, of the FMRP protein (Hagerman, 1996; Hagerman & Hagerman, 2002). Therefore, the disorder in females is less severe than in males. A female can typically learn to read, but often without self-monitoring, resulting in minimal comprehension. For females with Fragile X, abstract concepts such as time and money are impossible to comprehend beyond the most basic level. Full mutation males, on the other hand, have no FMRP protein and thus are severely affected. A typical full mutation grown Fragile X man has the mental capacity of a toddler or a preschooler. It is not clear why, but some Fragile X men have some CGG repeats in the premutation level, i.e. below 200, in addition to the dominant full mutation, above 200, CGG repeats. This allows for some level of

FMRP production in their bodies. These males are known as mosaics. They are higher functioning than non-mosaic Fragile X men, but lower functioning than full mutation Fragile X females (Hagerman & Hagerman, 2002).

While most parents discuss their children's diagnosis in terms of the CGG repeats, the underlying biochemistry is more complicated than that. Cells in our bodies chemically modify the DNA in order to control genetic information. One method of doing so is through inactivating part of a chromosome through adding methyl groups to it. This approach addresses an issue in females since they have two X chromosomes. Instead of over producing protein from the information on the two X chromosomes cells, the female body randomly picks one of the X chromosomes and turn it off via the methylation process. As such, both males and females have one working X chromosome in each cell (NFXFb, n.d.). The National Fragile X Foundation explains how bad methylation triggers the Fragile X characteristics (NFXFb, n.d.):

“Near the FMR1 gene is a regulatory site called a CpG island. In most people, the site is not methylated. As a result, the cell can use the FMR1 gene when there is a need for FMRP – The Fragile X Protein. In people with fragile X syndrome, the CpG island is methylated. As a result, the cell is unable to copy the information in the FMR1 gene. Since an mRNA copy is not made, FMRP will not be synthesized. Since there is no FMRP at the time and place it is needed, the characteristics of fragile X syndrome are set in motion.

In theory, if the methylation could be removed from that spot on the FMR1 gene, it could allow access to the FMR1 gene and allow its FMRP product to be assembled. This is one of the potential treatment areas that researchers are investigating.”

The story of methylation does not end here. As mentioned, in females the cells use methylation to turn off one copy of the X chromosome. In Fragile X females one of the X chromosomes will have a full mutation. If a larger number of cells turn off the mutated X chromosome then those cells will be able to produce the Fragile X Protein and the female will be less severely affected. If a large number of cells turns off the normal X chromosome then the mutated X chromosome will not be able to generate the Fragile X Protein and the female will be more severely affected. (NFXFb, n.d.). This randomness, at least what we currently perceive as random, nature of methylation in addition to the unpredictable nature of the CGG expansions is what causes the spectrum in the syndrome.

Fragile X has no known cure though there are some theories that could lead to pharmaceutical drugs offering some help. Research based on the FMR1 knockout mouse indicates that Fragile X is characterized by excess synaptic signaling activity. Bear, Huber, and Warren (2004) presented the “mGluR theory” proposing that “many of the protein-synthesis-dependent functions of metabotropic receptors are exaggerated in fragile X syndrome.” Thus, many of the Fragile X symptoms can be accounted for by excessive signaling by group I metabotropic glutamate receptors (Dölen, 2005). This resulted in an effort to develop drugs that inhibit or block GpI mGluRs specifically mGluR1 and mGluR5. Since mGluR1 is critical for proper cerebral functioning the research effort focused on blocking mGluR5 (Dölen, 2005).

Unfortunately, while the theory sounds appealing and while results have been very successful in lab experiments on mice (Dölen, 2005) none of the human trials yielded any positive results, and as of 2015, most of the trials have been cancelled or failed to move on to the next stage. It is not clear why the drugs have failed in human trials. One argument can be made that the human brain is so much more complex than the mouse brain such that drugs that worked

in the mouse could not work in humans. However, the world leading Fragile X clinical researchers have taken the position that the failure is in measuring outcome in those short duration studies and not in the drugs themselves.

While we lack information on the long-term effects of Fragile X on individuals and their families, a recent report from the A. J. Drexel Autism Institute titled “National Autism Indicators Report: Transition into Young Adulthood. 2015” provides insight into the long-term effects of Autism (Roux et al., 2015). According to the Drexel report young people with autism are facing significant challenges after high school. More than a third of young adults with autism in the study did not work nor pursue post high school education. Fewer than a third of those young adults have ever lived apart from their parents. One fourth receive no support services at all, and the same percentage reported being socially isolated, not having received any invitations for social activities within the prior year. The ones that did work typically worked in part time and low paying jobs. Incidentally, the 68-page report is based on data collected in two government studies, one a national longitudinal transition study and the other being a survey. Generally speaking, researchers found that there is very little that is known about how adults with autism fare as they transition into adulthood or about how to best provide services or help them live fulfilling lives (Roux et al., 2015). One quote from the report, by associate professor Paul Shattuck, stands on its own as the main reason as to why it is critical to collect and study the longitudinal data: “A critical next step is to figure out what facilitates connections to outcomes and what helps people to continue to succeed across their early adult years.”. Farley et al. (2017) investigated outcomes for individuals with autism in their 30s and 40s and found that members of this population continue to find it difficult to live independently, maintain employment, or sustain relationships.

While the research on Fragile X is limited, we know that individuals with Fragile X face bigger challenges than the general Autism population and have much fewer resources dedicated to them. In fact, children with Fragile X are classified as “other health impaired” in Individual Education Plans at their schools because Fragile X is not even recognized as its own impairment.

To address the need for collecting information about Fragile X patients and their caregivers, the CDC has funded the development of the “Fragile X Registry with Accessible Research Database” (FORWARD). The FORWARD database is open only to individuals diagnosed with Fragile X syndrome. As the CDC readily acknowledges (CDC, 2014), most parents spend years taking their children from one doctor to another before expensive testing and expert neurologists can provide proper diagnosis. Prior to official diagnosis many children receive early intervention services through state agencies and are frequently asked many of the same questions the CDC seeks to answer, but with no systematic or centralized mechanism to collect and retrieve the answers.

The FORWARD database mostly collects information annually for newly diagnosed patients. Typically, as children grow older and parents adjust to their new realities they do not make the annual trip to the Fragile X clinic, thus eliminating the data collection in its entirety. The transition from annual to no visits results in very little information collected on young adults with Fragile X and even less information as they get older (CDC, 2014). This pattern of annual evaluation is not specific to the FORWARD database. In a three-year longitudinal study, Hernandez et al. (2009) evaluated 56 boys only once a year each. Thus, over the span of three years, the children were evaluated a total of three times each. The MIND institute at UC-Davis, in May of 2015, announced a longitudinal study of male carriers of Fragile X ages 40 to 75. The study involves a mere three visits over the span of five years.

Participation in the CDC database is limited only to Fragile X clinics that are members of the Fragile X Clinical Research Consortium (FXCRC). As of December 2014, there were only 27 such Fragile X clinics, all in the continental United States with a disproportionate concentration in the Northeast and Midwest of the United States. Most states do not have a clinic, and there are no clinics outside of the United States. As a result, access to clinics and in turn the FORWARD registry is severely limited to families in geographic proximity or to well-to-do families willing to travel to the clinics. The FORWARD database went online in 2008, yet in 2014 it only had 500 Fragile X individuals in the database (Armour, 2014).

The FORWARD database and similar clinical longitudinal data collection systems collect only information in standardized forms. This stems from the fact that it is easier to develop analysis systems based on standardized questionnaires and that it is easier for government agencies to draw conclusions from a pre-designed set of questions. The CDC acknowledges that we know little about the patient population. As such presuming that we know what questions to ask eliminates all the scenarios of which we are not yet aware (Kaplan and Saccuzzo, 2009).

Khlat, Legleye, and Sermet (2014) found that men with lower levels of education are less likely to self-report on mental health problems when distressed. While this study did not reference Fragile X, men with Fragile X are always lower educated and suffer from anxiety and other mental health issues. It is reasonable to expect that if men with normal cognition were less likely to self-report then men with Fragile X having lower cognition and lower education are also less likely to report on mental health issues. Kirscht (1971) illustrated the inadequacy of self-respondent reports for several reasons including biases and inadequate reporting. Kooiker (1995) studied different survey methods for self-reporting occurrences of everyday illnesses. The study compared checklist questionnaires to open-ended diary style answers. The study confirms the

mismatch between the two methods, and posits that the respondent's psychological distress has a higher effect on checklist surveys than open-ended diaries, while diaries lead to underreporting due to the higher levels of compliance. The study also found that less educated subjects who suffered from chronic conditions were less likely to record results in diary format. Finally, psychological distress was found to have a great effect on the response patterns (Kooiker, 1995).

From a human factors point of view, the experience of completing a terse questionnaire during stressful clinic visits is not a pleasant one; it leads to cognitive overload, and results in poor quality responses. When visiting clinics, caregivers are typically asked to fill in multiple questionnaires in addition to the FORWARD questionnaires. Those questionnaires collect data pertaining to the clinic's records themselves, the host hospital, or the primary investigator's research purposes. Those questionnaires, developed by disparate parties, often contain duplicate questions, differing scales for similar questions and occasionally conflicting questions. This adds to the stress level of the caregiver and further contributes to reduction of accuracy of the results. Exacerbating the issue, caregivers of children with special needs in general, and children with Autism Spectrum Disorder, in particular, end up being asked similar questions by their pediatricians, school psychologists, Individualized Education Plans (IEP) providers and private therapists. A concerned parent, engaged in their child's well-being, can potentially answer similar sets of questions for a dozen parties each year, almost invariably under stressful conditions. None of those parties share information with each other or coordinate the questions or the scales. Those assortments of issues result in Choice Fatigue. Humans can only make a finite number of choices before cognitive overload results in "default" or "poor" selections.

Language Sample Analysis

Children with an Autism Spectrum Disorder often require intensive speech and language therapy at a young age (Vismara, Colombi, and Rogers, 2009). To conduct effective therapy, Speech and Language Pathologists (SLP) conduct one-on-one or small group sessions to work with these children. Pre-assessments are required to evaluate each child's current abilities to create a proper plan of care (Purse & Gardner, 2013). However, many children with Autism Spectrum Disorder also suffer varying levels of social and other anxieties (Kim et al., 2000), making it difficult to conduct a valid pre-assessment of the children's language and speech abilities, which in turns makes it impossible to curate an effective plan of care. The challenges are compounded in the subset of children with Autism Spectrum Disorder who are concurrently cognitively impaired. Unfortunately, those children would not understand the importance of the pre-assessment, an understanding that may lead an otherwise anxious child to try to overcome her anxiety. Further complicating matters is the therapist's inability to distinguish between whether the lack of response from the child is due to the child's speech and language deficit versus lack of response due to social anxiety versus lack of response due to cognitive impairments. As speech and language sessions are not affordable, neither in terms of time nor money, the built-up frustration often leads to ineffective services or, worse yet, to discontinuation of services.

Language Sample Analysis (LSA) has long been considered a critical tool for speech and language clinicians to evaluate expressive language abilities in children presenting with speech and language difficulties (Price, Hendricks, and Cook, 2010; Leadholm & Miller, 1994;

Superduperinc.com, 2018). Policy and educational guidelines dictate use of multiple assessment methods to evaluate speech and language and mandate authentic assessments reflecting true abilities of children (Price, Hendricks, and Cook, 2010). LSA is not the only evaluation tool available to speech and language therapists; in fact, other standardized assessments are used in the evaluation (Purse & Garnder, 2013). However, the LSA provides a great deal of useful information about the client's language ability including conversational skills, grammar, word meanings, social skills and morphology (Cdswebserver.med.buffalo.edu, 2018). Current clinical practices for conducting a language sample analysis either utilize manual sampling and assessment by clinicians or utilize recording devices, transcription software and automated assessment software (Tatenhove, 2014). Children with anxiety disorders, or selective mutism, typically fail to provide authentic samples to the SLP. Similarly, non-verbal children cannot provide spoken samples rendering current approaches to evaluation ineffective for them. In a typical assessment session, the therapist elicits language samples from children (or adults) through guided conversations. Often showing a picture and asking the child for a description of the picture (Ling-Yu Guo, n.d.). Figure 5 depicts the famous cookie theft picture that has been used to illicit language samples in language therapy for decades (Cooper, 1990). The conversation with the child is recorded via an audio recording device. The therapist then transcribes the conversation and finally uses a PC-based software to analyze the language sample (Ling-Yu Guo, n.d.). The SLP requires great effort to have a faithful transcription of the spoken text, including all mistakes. The transcription process itself can introduce human errors on the part of the SLP; thus, the final transcription may not be exact due to transcription errors and subjective errors in interpreting mispronunciations, unclear speech and stops in the spoken language. Studies have shown that, while the approach is academically popular, it is not

commonly used in practice. The current procedure involves recording devices, commercial PC-based software that is not straightforward to use, and manual transcriptions, all of which add overhead to the process and can lead to errors (Price, Hendricks, and Cook, 2010).

Studies show that even though most SLPs use Language Sample Analysis, fewer than 10% of SLPs use computerized mechanisms to analyze language samples (Price, Hendricks, and Cook, 2010). The most likely reasons for lack of utilization are difficulty of use, lack of familiarity and training, cost, and issues with transcriptions. Price, Hendricks, and Cook (2010) present a four-step tutorial on using one specific software to conduct LSA. The tutorial unveils the complexity and effort involved in carrying out the process. Keeping in mind that an LSA is typically only one of several assessment techniques, all of which must be conducted in a very short time span, typically under 30 minutes; we can understand why most SLPs elect to use the manual process in lieu of the automated process.

There are not many resources available for automated analysis of speech samples, the few that exist are PC-based commercial programs that need to be purchased and installed on the SLP's computer. While, without doubt, the commercial software packages offer strong research-based analysis and databases of samples for comparison, they were developed prior to recent innovations in natural language processing and mostly operate based on tokenizing and counting of words. They all operate on the same principal approach of an SLP prompting for a speech sample, the SLP recording the speech sample using a direct recording device or as part of an Augmentative and Alternative Communication (AAC) device, the SLP transcribing the recording either manually or using a speech to text software and then finally using the PC-based software to analyze the transcribed sample.

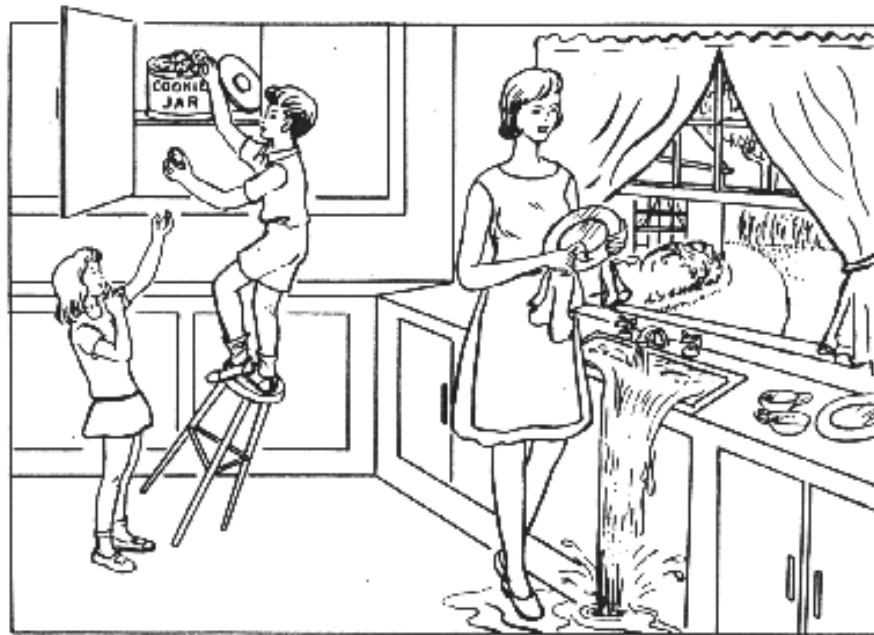
In addition, Tatenhove (2014) outlines six issues with language sample collection and analysis using AAC devices:

- Validity of Automatically collected data
- Elicitation Methods
- Length of Language Samples
- Defining utterances
- Calculating Mean Length of Utterance
- Language Sample Analysis Software

Those issues identified by Tatenhove (2014) are compounded when dealing with children with intellectual disabilities and social anxiety. Children suffering heightened anxiety and social disorders, such as those with Autism Spectrum Disorder (ASD) or having the Fragile X syndrome disorder present especially difficult challenges to SLPs when attempting to solicit language samples. The challenges turn from difficult to impossible when presented with non-verbal or selectively mute children. The astute reader may question the need for speech therapy for non-verbal children. However, non-verbal children have been taught to read silently and to express themselves in writing. The fact that their expressive communication is mostly limited to written communication makes it even more critical that they receive help with their expressive language even if speech is not an option.

The Natural Language Toolkit (Bird, 2006; Nltk.org, 2018) is developed in Python and is a leading platform for working with human languages. The NLTK provides easy access to more than 50 corpora. It has an idiomatic Python API that allows Python developers to easily build and integrate software that utilizes the NTLK's numerous natural language processing abilities. The authors of the NLTK, Steven Bird, Ewan Klein and Edward Loper have also written an

excellent book (Bird, Klein, & Loper, 2009) titled “Natural Language Processing with Python – Analyzing Text with the Natural Language Toolkit,” which was the inspiration for the framework presented in this dissertation. The NLKT works with Python 3 as well as Python 2.6/2.7. Our development efforts have been done in Python 3.



Source: <https://aspieantiquarian.wordpress.com/2015/01/01/the-boston-cookie-theft/>
Figure 5: The famous cookie theft image often used to elicit language samples by language therapists.

Recently researchers have started to collect social media discourse to conduct language and sentiment studies. Verheijen and Stoop (2016) created a corpus of Facebook and WhatsApp social discourse by Dutch youths between 12 and 23 years old to study the linguistic features of those posts. Verheijen and Stoop collected the data by providing a web site for Dutch youth to donate their chats and built a Facebook app to collect Facebook chats programmatically from the

contributing youths once their consent was attained. Mitra and Gilbert (2015) compiled a corpus of tweets based on tracking more than 1 billion streaming tweets over the period of more than three months correlating them with global events. Simpson, Adams, Brugman, and Conners (2018) conducted a study on roughly 884.2 million tokens from a twitter data set collected in 2016. The goal of the study was to conduct natural language processing to discover drug terms previously unknown to researchers that are in use in social media.

Video Modeling

In vivo modeling, the process of one person observing another person engage in a target behavior or apply a functional skill has been shown effective in teaching neurotypical children (Charlop-Christy, Le, and Freeman, 2000). In the special needs population, research on applying modeling has mostly focused on children with autism. Initial research did not show efficacy for using modeling in teaching children with autism. However, subsequent studies have consistently shown efficacy for this approach in this population (Charlop-Christy, Le, and Freeman, 2000). Video modeling applies technology to the modeling procedure by recording a video of the desired model for children to later watch (Ogilvie, 2011). Video modeling compares favorably with in vivo modeling for children with autism. It allows the children to focus on the target behavior or skill while reducing distractions caused by external stimuli (Ogilvie, 2011). Unlike in vivo modeling, video modeling can be replayed repeatedly benefiting children with autism who generally learn better through repetition (Ogilvie, 2011). Video modeling produces less social anxiety for children with autism than in vivo modeling (Ogilvie, 2011). It is also generally more efficient and economical to have a pre-recorded video that can be reused than to have a person model behaviors on demand. While not addressed in published research, it is also logical

to assume that a library of professionally developed video models can be beneficial for use across multiple schools and classrooms instead of having teachers recording their own videos. Charlop-Christy, Le, and Freeman (2000) showed that video modeling led to faster acquisition of tasks when compared to in vivo modeling and promoted generalization.

Buggey (2005) conducted a study with five participants on the autism spectrum, in a small private school settings, using video self-modeling and showed that all participants had significant gains that endured past the termination of the video modeling intervention. More recently, Schaeffer, et al. (2016) reviewed the literature covering video self-modeling interventions, illustrating that the approach has been shown effective in numerous studies, while being especially suited for children with autism.

Bellini and Akullian (2007) conducted a meta-analysis of 23 different single subject studies that studied efficacy of video modeling and video self-modeling on children and adolescents with autism. They concluded that both video modeling and video self-modeling are effective intervention strategies for addressing behavioral challenges as well as for acquiring new skills. Bellini and Akullian (2007) confirmed that skills acquired via video modeling and video self-modeling strategies were maintained over time.

A gap exists between scientific research on interventions for students with special needs and what is applied practice in classrooms for students with special needs (Greenwood & Abbott, 2001). Video modeling represents an example of this chasm. While it has been validated multiple times as an effective approach to teaching students with special needs new skills (Ogilvie, 2008; Ogilvie, 2011), aiding them in self-control and reduction of interfering behaviors (Buggey, 2005), it is very seldom used in classrooms for students with special needs (Abualsamid & Hughes, 2017). Schaeffer, et al. (2016) argued that such interventions are not implemented with

efficacy in real life education settings due to the demands on the educators' time and resources. Schaeffer, et al. (2016) provided practical guidelines for effectively implementing the intervention in educational setting. We argue that human factors, lack of systematic procedures, and lack of tools present barriers for teachers to practically utilize video modeling in classrooms. Analytics are the cornerstone of special needs interventions, yet there are no standardized frameworks, tools, or procedures, to guide teachers in analyzing the long-term effects of their interventions.

While the cited research provides evidence for effectiveness of video modeling in promoting skills acquisition and reducing interfering behavior, special needs educators lack a structured mechanism for applying such interventions in their real-life classrooms. Ogilvie (2011) describes a 10-step process for effectively implementing video modeling for students with Autism Spectrum Disorder (ASD):

1. Identify the target behavior.
2. Collect baseline data.
3. Choose competent peers to help create the videos.
4. Secure permissions and consent.
5. Prep the peer models.
6. Prepare the environment.
7. Create the video.
8. Intervene.
9. Gather data.
10. Assess and reflect.

Indiana University Bloomington (n.d.) has a nine-step implementation guide that can be used by teachers in their classrooms when applying video self-modeling interventions:

1. Choose a behavior to target.
2. Gather the correct equipment.
3. Collect baseline data.
4. Plan the video recording.
5. Record the video.
6. Determine the environment and day for watching the video.
7. Show the video.
8. Collect data to monitor progress.
9. Fade the video as needed.

In our view, the laborious steps, along with the already extensive demand on teachers of students with special needs time constitute barriers to widespread utilization of video modeling interventions in classrooms for students with special needs.

Technology in Classrooms for Students with Special Needs

Research shows that special needs teachers are willing to utilize technology in their classrooms when it is accessible and easy-to-use (Abualsamid & Hughes, 2017). While research on using technology for interventions in classrooms for students with special needs is scant, we do have data on using technology to support learning in classrooms for students with special needs. Liu, Wu & Chen (2013) conducted a meta study of 26 journal papers published between 2008 and 2012 addressing the use of learning technologies in classrooms for students with special needs, and they concluded that 75% of the published research aimed to determine the

effectiveness of using learning technologies in classrooms for students with special needs. Liu, Wu & Check found that of the 21 papers that aimed to study the effectiveness of learning technologies in classrooms for students with special needs, only two showed a negative outcome, one was neutral and the rest showed positive outcome for using learning technologies in classrooms for students with special needs (Liu, Wu & Chen; 2013). The aforementioned meta study informs us that special needs teachers do utilize technology in their classrooms when it is accessible and effective.

Realizing the need for modern technology in classrooms for students with special needs, Fernández-López, et al. (2013) developed an iOS based mobile learning platform for students with special needs and successfully conducted a pre-experimental study with 39 students that showed the efficacy of using mobile learning technologies in classrooms for students with special needs. Campigotto, Mcewen, & Epp (2013) used a mobile app called MyVoice, an augmentative and alternative communication app that can be used to speak phrases based on context and linked images, in a five-month exploratory study in two classrooms for students with special needs and concluded that there is a strong potential for integrating technology into classrooms for students with special needs (Campigotto, Mcewen, & Epp, 2013). We surveyed 44 special needs educators across several schools for students with special needs on their familiarity with video modeling interventions for students with special needs and their own use of video modeling. We found that only 25% of the educators were familiar with video modeling and only 1 out of 44 educators used it in their classroom. The result of the survey indicates that human factors play a major role in discouraging educators familiar with video modeling from using it in their classrooms (Abualsamid & Hughes, 2017).

The aforementioned research shows that technology in classrooms for students with special needs can be effective. But, while technology is used for academic learning applications it is seldom used to conduct interventions to reduce interfering behaviors nor to teach life skills. Specifically, research shows that video modeling in particular is seldom used for either purpose in real life classrooms.

In their seminal work, Baer, Wolf and Risley (1968) listed seven characteristics of Applied Behavioral Analysis: Applied, Behavioral, Analytic, Technological, Conceptually Systematic, Effective and General (Baer, Wolf, and Risley, 1968). In 2005, Heward (2005) suggested augmenting the original seven characteristics by adding: Accountable, Doable, Public, Empowering and Optimistic. During the early days of Applied Behavioral Analysis, Lovaas conducted foundational long-term research in Applied Behavioral Analysis and based on long-term results suggested improvements to the then common approaches by utilizing interventions at earlier age, involving the parents in the interventions and applying interventions at home (Smith and Eikeseth, 2011).

Informed by the experts work in Applied Behavioral Analysis, we propose that developing a systematic technology framework and a set of easy-to-use tools would increase the use of technology for applying interventions in classrooms for students with special needs, and would allow such interventions to adhere to the relevant characteristics of Applied Behavioral Analysis as introduced by Baer, Wolf and Risley (1968) and as augmented by Heward (2005), while also adhering to Lovaas's suggestions of involving the parents in the interventions and applying interventions at home.

Conversational Chatbots

Since Alan Turing proposed the imitation game as a replacement for the question of “can machines think?” researchers have been interested in developing chatbots (Mauldin, 1994). Wallace (2009) described the anatomy of the Artificial Linguistic Internet Computer Entity, aka A.L.I.C.E., which won the prize as the “most human computer” at the annual Turing Test contests in the years 2000, 2001, 2004 (Wallace, 2009). Higashinaka et al. (2014) recently described an open-domain architecture based on natural language processing that allows a chatbot to understand utterances and formulate a response without using hand-crafted rules. Conversely, Mhatre, Motani, Shah, & Mali (2016) described an architecture for a task specific web based chatbot that aids the user in scheduling calendar events. There is no published research, that we are aware of, on using conversational chatbots with individuals with special needs.

Augmentative and alternative communication devices, such as storyboards, communication boards, and picture exchange communication systems are often used with persons with Autism Spectrum Disorder, as well as people with cognitive disabilities, to aid in dealing with communication and language challenges such as repetitive questions, echolalia, anxiety, short-term memory challenges and cognitive challenges (Flippin, Reszka, & Watson, 2010; Light, Roberts, Dimarco, & Greiner, 1998; Dooley, Wilczenski, & Torem, 2001). Amazon Lex is a new service from Amazon Web Services (AWS) for building conversational interfaces through parsing utterances and inferring intents. Amazon Polly is another recent service from AWS that turns text into lifelike speech, allowing for the development of applications that speak in a natural, lifelike speech. AWS Lex and Polly are built on the same technologies that power the Amazon Echo, more commonly known as Alexa, an artificial intelligence powered device that sits at homes or offices and responds to spoken commands, such as “what’s the weather like

today”, and allows for home automation (Dempsey, 2015). The nascent nature of all those technologies means there is no published research yet on how persons with autism interact with those devices. The author’s anecdotal experiences, including with his own two children with Fragile X and co-morbid autistic behaviors, show that persons with autism tend to interact with Alexa as they would a person, asking it questions, greeting it in the morning, and requesting home automation commands from it. Google recently released similar devices, called Google Home Mini and Google Home Max, and Apple released their own device, HomePod. The proliferation, affordability, easy setup, and natural, conversational interface of those devices, makes them natural candidates for developing conversational assistive technologies for persons with autism and related disorders (Perez, 2017).

CHAPTER THREE: ANALYSIS OF SOCIAL DISCOURSE FRAMEWORK

Overview

The open-source Analysis of Social Discourse (ASDF) framework, that we developed is available at <https://github.com/abualsamid/lisa>. It has a permissive license allowing it to be used for any research purpose, as well as allowing for pull requests if contributors want to improve the software. The Python program can be pointed to a data folder that contains individual text files with language samples in them. The program will loop through the files in the folder, and, for each file, will provide analytical metrics that can be used by the SLP to assess the child. The rest of this section will describe the different metrics and statistical data generated by the software. The framework is built on top of the Natural Language Processing Toolkit (NLTK) (Nltk.org, 2018), a popular python based natural language processing toolkit that was developed in part to enable research such as the work described in this paper. In order to demonstrate the features of the ASDF we will use a famous “think different” poem used by Apple, Inc. in its marketing campaigns in 1997 and 1998 (Shields, 2001). For reference, we quote the poem below.

“Here’s to the crazy ones.

The misfits.

The rebels.

The troublemakers.

The round pegs in the square holes.

The ones who see things differently. They’re not fond of rules.

And they have no respect for the status quo. You can praise them, disagree with them, quote them,

disbelieve them, glorify or vilify them.

About the only thing you can’t do is ignore them.

Because they change things.

They invent. They imagine. They heal.

They explore. They create. They inspire.
They push the human race forward.

Maybe they have to be crazy.
How else can you stare at an empty canvas and see a work of art?
Or sit in silence and hear a song that's never been written?
Or gaze at a red planet and see a laboratory on wheels?
We make tools for these kinds of people.

While some see them as the crazy ones,
we see genius.
Because the people who are crazy enough to think
they can change the world, are the ones who do.”

Tokens, Words, Sentences, Stems and Lemmas

The framework uses the NLTK to tokenize the input text into words, sentences, stems and lemmas as shown in our sample Python code, which is incorporated from examples in the NLTK book (Nltk.org, 2018), below:

```
import nltk

from nltk.corpus import PlaintextCorpusReader

from nltk import word_tokenize

corpus_root = '/sla/data'

wordlists = PlaintextCorpusReader(corpus_root, '.*')

for fileid in wordlists.fileids():

    raw = wordlists.raw(fileid)

    sents = wordlists.sents(fileid)

    tokens = word_tokenize(raw)

    words = [lower() for w in tokens]
```

```
vocab = sorted(set(words))
porter = nltk.PorterStemmer()
stems=sorted(set([porter.stem(t) for t in tokens]))
wnl = nltk.WordNetLemmatizer()
lemmas = sorted(set([wnl.lemmatize(t) for t in tokens]))
num_chars = len(raw)
num_words = len(words)
num_sents = len(sents)
num_vocab = len(vocab)
```

In few lines of code, we have examined a sample text, tokenized it into words, split it into sentences, found the unique set of vocabularies used in the text, found all the stems the child produced in the text as well as all the lemmas, and produced various statistics regarding the length of the raw text, the number of words, the number of sentences and the number of unique vocabulary words used. The stems and lemmas are important from a morphology point of view in giving us more insight into the child's language breadth and depth as they remove the variations of lexical usage to focus on the origin of the word. Lemmatization performs morphological analysis and removes inflectional endings to discover the base form of a word. Stemming uses heuristics to remove the ends of words to discover their base form.

Complexity and Diversity

In addition to discovering the information above regarding the raw data, the framework uses the NLTK to produce the average length of words used, the average length of sentences, aka

Mean Length of Utterances (MLU) in language therapy, as well as the lexical diversity of the text, which is defined as the number of unique words, i.e. vocabulary, divided by the total number of words used in the text.

Frequency Distribution

An important element in measuring the quality of language production, and more importantly in measuring the progress of language production over time is the frequency distribution of words used and the frequency distribution of lengths of words used in language production. For example, in Table 1, we present the frequency distribution of words used in the “think different” poem quoted above. The distribution shows words and punctuation symbols along with the frequency of usage of each, ordered from most frequent to least frequent. The full analysis produced by our framework for this poem is presented in APPENDIX B: FULL LANGUAGE SAMPLE ANALYSIS OF THINK DIFFERENT POEM. Another frequency distribution of interest to us is the distribution of lengths of words. For our example above, the frequency distribution of the length of words used is presented in Table 2. What the information in Table 2 tells us is that 3, 4, and 1 letter words make up the vast majority of the sample. A single sample is not adequate to draw conclusions but this is another metric that can be very useful in longitudinal studies to understand changes over time to the child’s language production.

Table 1 Frequency Distribution of Words in the Think Different poem

Words	Frequency of Occurrence
.	22
The	14
They	12
Them	7
,	6
See	5
,	4
Crazy, ones, and, can, a	4
To, who, of, you, or, ?	3
S, in, things, have, for, do, because, change, at, we, people, are	2
Here, misfits, rebels, troublemakers, round, pegs, square, holes, differently, re, not, fond, rules, no, respect, status, quo, praise, disagree, with, quote, disbelieve, glorify, vilify, about, only, thing, t, is, ignore, invent, imagine, heal, explore, create, inspire, push, human, race, forward, maybe, be, how, else, stare, an, empty, canvas, work, art, sit, silence, hear, song, that, never, been, written, gaze, red, planet, laboratory, on, wheels, make, tools, these, kind, while, some, as, genius, enough, think, world	1

Table 2 Frequency Distribution of length of words for the Think Different poem

Length of Word	Frequency of Usage
3	43
4	42
1	42
2	24
5	21
6	19
7	11
10	2
13	1
11	1
8	1

Other frequency distributions provided by our framework are the frequency distribution of individual letters, which may be helpful in studying the use of vowels in text. Usage of letters such as v and w may indicate more breadth of language usage. Hapaxes, which are a special frequency distribution of one occurrence, are also generated by the framework as a separate metric.

Part of Speech tags

The NLTK includes a Parts Of Speech (POS) tagger (Bird, Klein, & Loper, 2009). A POS tagger processes words in text and assigns a part of speech to each word such as a noun, an adjective, coordinating conjunction, adverbs, etc. Similar to frequency distributions of words and length of words, the POS tags can provide insight to the content and depth of language samples, though it has not been traditionally used by SLPs, as such it is an added metric that affords the SLPs more insight into evaluating the language samples. Like Frequency Distributions, the Part of Speech tagging may not be insightful for a standalone language sample; however, it can provide insight into the evolution of language ability over time in longitudinal studies. The framework uses the NLTK to tag parts of speech and provide an output describing the part of speech tag of every word in the input sample as well as the list of words associated with each tag. For example, it provides lists of nouns, verbs, adverbs, etc. used in the input sample.

Misspellings

The NLTK employs the Words Corpus that is available on most Unix like systems at /usr/share/dict/words. By using this corpus, we can test for misspelled or unusual words in the sample text by looking for words in the text that do not appear in the Words Corpus. This, however,

is system dependent. For example, on Mac OSX the default Words Corpus is based on the Webster's 2nd International dictionary which spells cookie as cooky. On Ubuntu the "wamerican" dictionary can be installed, which provides for less than half the words of the version on Mac OSX, but includes more commonly spelled American English words such as cookie. Our framework uses the default system Words Corpus to provide a list of misspellings in the language sample. This metric is useful in both judging current spelling ability as well as progress over time.

Stopwords

Stopwords refer to high-frequency words that usually have no lexical content. The NLTK has a corpus of Stopwords. The English list is reproduced below for reference directly from the NLTK:

'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', 'your', 'yours', 'yourself',
'yourselves', 'he', 'him', 'his', 'himself', 'she', 'her', 'hers', 'herself', 'it', 'its', 'itself',
'they', 'them', 'their', 'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that',
'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had',
'having', 'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as',
'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through',
'during', 'before', 'after', 'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off',
'over', 'under', 'again', 'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why',
'how', 'all', 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some', 'such', 'no', 'nor',
'not', 'only', 'own', 'same', 'so', 'than', 'too', 'very', 's', 't', 'can', 'will', 'just', 'don', 'should',
'now'

For our purposes, we define content words as words in the language sample that are not Stopwords. Our framework provides a metric for the percentage of content words relative to the whole text. In the USA, English language speakers use Stopwords for roughly 60% of their speech. The Framework allows us to understand what percentage of the language sample is content and what percentage is Stopwords which would give us insight to how the child performs against the average English speaker in the country.

Research on social media discourse has proliferated recently (Verheijen & Stoop, 2016; Mitra & Gilbert, 2015; Simpson, et al., 2018; Townsend & Wallace, 2016). This has led to questions regarding what's appropriate to use in research. Townsend and Wallace (2016) of the University of Aberdeen published a book entitled: *Social media research: a guide to ethics*. In the book, they describe a framework to evaluating appropriate use of social media content in research. In order to validate the ASDF framework we need to execute the tools against language samples. This process validates the framework's ability to conduct language sample analysis using natural language processing. For this evaluation, we choose the following language samples: The abstract of this dissertation, found at the beginning of this document. A public blog post by the author of this dissertation available on his company's website. The "think different" poem used by Apple in an advertisement campaign in 1997, 1998. To obtain external resources, while adhering to the framework set by Townsend and Wallace we also chose a public blog, published under a pseudonym, by an adult with autism who is advocating for individuals with autism. This social media source is both public and anonymous. We further do not publish the pseudonym, nor the data set, and we do not identify the blog. We only publish 14 summary metrics related to language sample analysis. For the final set of data, we selected public Facebook posts of a public figure in the technology industry with over 100 million followers.

Similarly, we do not publish the identity of the author, nor the data set, nor any identifying data, but only the 14 metrics to related to language sample analysis.

The study was conducted to evaluate the framework's ability to provide metrics helpful in analyzing language samples and not to analyze the quality of the data sets; any data sets from social media would've worked for this purpose. To reduce dependencies on operating system dictionaries and corpus, the study was done using the python:3 docker image from the official docker repository available at https://hub.docker.com/_/python/. The Dockerfile used to conduct the study, as well as the source code, is available in the author's github repository accessed at: <https://github.com/abualsamid/sla>, allowing other researchers to replicate the study if need be.

Results and Discussion

To validate the ASDF framework we analyzed the abstract of this dissertation, available at the beginning of this document, a public blog post by this author, on his company's blog, and four public social media postings each from two different sources, for a total of 10 samples. While the latter two sources are publicly available, we are not identifying the sources, the data were not retained, though it is still available publicly, and no identifying information was included in the analysis. The first source was a public blog by an adult with autism published pseudonymously and meant to be read widely as it is advocating for the causes of individuals with autism. The second source was from a public figure in the tech industry with millions of followers. The goal of the study is to validate the framework's ability to conduct language

analysis and not to comment on the specifics of the chosen posts. Any public social discourse could have been chosen for the study.

Table 3 has the results of analyzing the first post. The framework displays more metrics such as frequency distribution of hapaxes (words that appear only once) and vowels used in text. For the purposes of this paper we list the most relevant metrics for Language Sample Analysis; however the complete analysis can be retrieved by running the software against a chosen text sample as shown in Appendix B, which has the results of running the tool against the “think different” poem. The first metric displayed is the average sentence length, which is the count of letters and punctuation elements in an average sentence in the language sample. The second metric, average word length, is also known as Mean Length of Utterance (MLU) in the parlance of language therapy. The framework provides information about parts of speech tags as identified by the NLTK, specifically the tags analyzed are: adjective, adverb, conjunction, determiner, existential, foreign word, modal verb, noun, proper noun, number, pronoun, preposition, “to”, interjection, verb, past tense, present participle, past participle, and wh determiner. The table shows that the most used tag of speech in the first sample is the tag “noun”, used 138 times. The frequency distribution longest word metric shows the length of the longest word used, 12 letters in this case, and the frequency of occurrence, two times in this case. This metric reports on frequency distributions, not specific words, so it is possible to have multiple, different, words of the same length, the frequency column in that case would include the total number of occurrences of all those words in the text. Specifically, in this example, the post could have had one 12 letter word used twice, or two different 12 letter words, used once each. The frequency distribution length of most used word metric indicates the most commonly used length of word in the sample. This is a frequency distribution and not specific to any word,

so if the words “cat” and “car” were used in the text, this metric would report 3 for the length and 2 for the frequency. In this specific instance, we learn that the sample contained 1 letter words more than any other word length, coming in at 302 total times in this text. The full output of the analysis, not included in this dissertation, will include the complete frequency distribution for all word lengths in the text. This text sample contained modal verb “can”, used twice. Modal verbs are: will, can, would, may, must, should. The total words in this sample text is 1318.

Lexical diversity is the ratio different stems to the total tokens. In other words, it measures the percentage of unique words used in the complete text. The lexical diversity of this sample was 0.3869. The number of characters and number of sentences are self-explanatory. The number of vocabulary refers to the sorted set of words, or the unique words in the sample. The percent of content words is the fraction of non-stop words to the total number of words. Finally, the words per vocabulary metric is the ratio of the total number of words to vocabulary words, the higher the number, the more re-use of words in the text. The last row in each table is not a language analysis metric but is the actual run-time it took for the tool to analyze the input samples. The analysis was done by grouping all samples. Thus, the 4.09 seconds of execution time listed in the first four tables all apply to analyzing the first four samples together, as the tool iterates through all samples in a given folder. For contrast, we put all ten samples in a single folder and re-run the analysis in 4.51 seconds. We then ran the analysis on an empty folder and it completed in 1.69 seconds, indicating that the start-up time for the docker container and the python run-time is about 1.69 seconds with a fraction of a second of additional run-time for each representative sample of social discourse. All run-times were measured on a Mac-Pro laptop, model year 2016, with 16 GB of memory and an intel quad core i7 processor.

The rest of the tables present analysis results for the other samples. As the goal of this study is to validate the framework and not to judge the samples, there is no relative comparison between the samples.

Table 3 Source One: First Public Blog Post Analysis

Metric	Value	Frequency
Average Sentence Length	9.15	
Average Word Length	4.55	
Most Used Tag	Noun	138
Frequency Distribution	12	2
Longest Word		
Frequency Distribution	1	302
Length of Most Used Word		
Most Used Word	.	142
Modal Verbs Used	Can	2
Total Words	1318	
Lexical Diversity	0.3869	
Number of Characters	6005	
Number of Sentences	144	
Number of Vocabulary	510	
Percent of Content Words	62.13%	
Words Per Vocabulary	2.584	
Execution Time	4.09 seconds	

Table 4 Source One: Second Public Blog Post Analysis

Metric	Value	Frequency
Average Sentence Length	11.47	
Average Word Length	4.43	
Most Used Tag	Noun	138
Frequency Distribution	16	1
Longest Word		
Frequency Distribution	1	540
Length of Most Used Word		
Most Used Word	.	146
Modal Verbs Used	Can, could, will	9, 2, 5
Total Words	1939	
Lexical Diversity	0.3115	
Number of Characters	8605	
Number of Sentences	169	
Number of Vocabulary	604	
Percent of Content Words	57.45%	
Words Per Vocabulary	3.210	
Execution Time	4.09 seconds	

Table 5 Source One: Third Public Blog Post Analysis

Metric	Value	Frequency
Average Sentence Length	14.51	
Average Word Length	4.27	
Most Used Tag	Noun	90
Frequency Distribution	13	3
Longest Word		
Frequency Distribution	1	234
Length of Most Used Word		
Most Used Word	.	52
Modal Verbs Used	Can, will	4, 1
Total Words	900	
Lexical Diversity	0.3977	
Number of Characters	3849	
Number of Sentences	62	
Number of Vocabulary	358	
Percent of Content Words	61.77%	
Words Per Vocabulary	2.513	
Execution Time	4.09 seconds	

Table 6 Source One: Fourth Public Blog Post Analysis

Metric	Value	Frequency
Average Sentence Length	13.13	
Average Word Length	4.65	
Most Used Tag	Noun	54
Frequency Distribution	13	3
Longest Word		
Frequency Distribution	1	175
Length of Most Used Word		
Most Used Word	.	56
Modal Verbs Used	Can, could	2, 3
Total Words	762	
Lexical Diversity	0.3792	
Number of Characters	3544	
Number of Sentences	58	
Number of Vocabulary	289	
Percent of Content Words	49.86%	
Words Per Vocabulary	2.636	
Execution Time	4.09 seconds	

Table 7 Source Two: First Public Facebook Post Analysis

Metric	Value	Frequency
Average Sentence Length	22.20	
Average Word Length	5.20	
Most Used Tag	Noun	140
Frequency Distribution	16	1
Longest Word		
Frequency Distribution	4	413
Length of Most Used Word		
Most Used Word	.	100
Modal Verbs Used	Can, may, will	6, 1, 15
Total Words	2265	
Lexical Diversity	0.2684	
Number of Characters	11782	
Number of Sentences	102	
Number of Vocabulary	608	
Percent of Content Words	59.64%	
Words Per Vocabulary	3.725	
Execution Time	3.73 seconds	

Table 8 Source Two: Second Public Facebook Post Analysis

Metric	Value	Frequency
Average Sentence Length	17.81	
Average Word Length	4.74	
Most Used Tag	Noun	26
Frequency Distribution	10	2
Longest Word		
Frequency Distribution	2	59
Length of Most Used Word		
Most Used Word	.	16
Modal Verbs Used	Can, will	1, 1
Total Words	285	
Lexical Diversity	0.5263	
Number of Characters	1352	
Number of Sentences	16	
Number of Vocabulary	150	
Percent of Content Words	54.38%	
Words Per Vocabulary	1.9	
Execution Time	3.73 seconds	

Table 9 Source Two: Third Public Facebook Post Analysis

Metric	Value	Frequency
Average Sentence Length	20.42	
Average Word Length	4.84	
Most Used Tag	Adjective	12
Frequency Distribution	9	2
Longest Word		
Frequency Distribution	4	31
Length of Most Used Word		
Most Used Word	The	11
Modal Verbs Used	Will	1
Total Words	143	
Lexical Diversity	0.6433	
Number of Characters	693	
Number of Sentences	7	
Number of Vocabulary	92	
Percent of Content Words	55.94%	
Words Per Vocabulary	1.55	
Execution Time	3.73 seconds	

Table 10 Source Two: Fourth Public Facebook Post Analysis

Metric	Value	Frequency
Average Sentence Length	18.58	
Average Word Length	5.09	
Most Used Tag	Noun	40
Frequency Distribution	18	1
Longest Word		
Frequency Distribution	3	57
Length of Most Used Word		
Most Used Word	.	17
Modal Verbs Used	Could	2
Total Words	316	
Lexical Diversity	0.5158	
Number of Characters	1609	
Number of Sentences	17	
Number of Vocabulary	163	
Percent of Content Words	60.75%	
Words Per Vocabulary	1.938	
Execution Time	3.73 seconds	

Table 11 Dissertation Abstract

Metric	Value	Frequency
Average Sentence Length	27.42	
Average Word Length	6.57	
Most Used Tag	Noun	37
Frequency Distribution	17	1
Longest Word		
Frequency Distribution	2	42
Length of Most Used Word		
Most Used Word	and	13
Modal Verbs Used		
Total Words	329	
Lexical Diversity	0.4529	
Number of Characters	2160	
Number of Sentences	12	
Number of Vocabulary	149	
Percent of Content Words	68.08%	
Words Per Vocabulary	2.208	
Execution Time	3.30 seconds	

Table 12 Author's Blog Post

Metric	Value	Frequency
Average Sentence Length	19.63	
Average Word Length	5.04	
Most Used Tag	Noun	68
Frequency Distribution	17	1
Longest Word		
Frequency Distribution	2	83
Length of Most Used Word		
Most Used Word	to	24
Modal Verbs Used	Can, will	5, 3
Total Words	471	
Lexical Diversity	0.4607	
Number of Characters	2374	
Number of Sentences	24	
Number of Vocabulary	217	
Percent of Content Words	59.02%	
Words Per Vocabulary	2.170	
Execution Time	3.48 seconds	

CHAPTER FOUR: VIDEO MODELING SURVEY

Overview

We posit that technology is not being widely developed, nor effectively utilized, to support children with special needs. However, one technology that has been studied and shown in research to be effective is video modeling. In video modeling, the child is shown a video of a model behavior with the goal of teaching the child a new skill or modifying a behavior. This process has been shown effective in published research. However, published research, as well as anecdotal evidence shows that video modeling is not commonly utilized in classrooms for students with special needs. We conducted an anonymous survey, using the Survey Monkey tool, of 44 special needs educators in central Florida. To reach the educators, we sent an email to school administrators at a public elementary school, two private schools for students with special needs, and one charter elementary school with a mixed population of neurotypical and special needs enrollment. We asked the administrators to forward the email to special needs educators in their schools. The administrator at the charter school offered, and we took her up on the offer, to forward the email to other charter school administrators that she knows. In total, we had 44 correspondents. Due to the anonymous nature of the surveys, we do not know which schools the respondents came from. The two private schools are schools that cater exclusively to students with special needs, each of the two schools has a total population of under 75 students and caters to students from 1st to 12th grade with classrooms containing children spanning multiple ages. The public school is a typical state public elementary school catering to children from pre-kindergarten to fifth grade. The school employs push style interventions, where special needs educators and therapists are pushed into a mainstream classroom, pull style interventions where students with special needs are pulled out of their mainstream classroom for small group

sessions, and inclusive classrooms for lower functioning students that cannot be mainstreamed. The charter school caters to students from pre-kindergarten to 5th grade. The school aims to have classrooms with roughly 50% mainstream students and 50% students with special needs in the same classroom being taught by the same teachers. As the survey was anonymous, with no tracking mechanisms by design, we do not know which schools the responses came from. The survey was conducted using the online survey system Survey Monkey (<https://www.surveymonkey.com>). The survey was open for 4 weeks during which we received 44 individual responses.

The survey contained the following eight questions:

- 1) Are you familiar with using Video Modeling Interventions in the classroom?
- 2) Are you using Video Modeling in the classroom?
- 3) Do you consider your current process for Video Modeling in the classroom efficient?
- 4) What do you like most about video modeling in the classroom?
- 5) What do you like the least about video modeling in the classroom?
- 6) Are you using apps for any purpose other than Video Modeling in your classroom, e.g. track behavior, track data, ...?
- 7) What do you like the most about using the other apps in your classroom?
- 8) What do you like the least about using the other apps in your classroom?

Responders who answered No to the first question were presented with question 6 next, skipping questions 2, 3, 4 and 5. Similarly, responders who answered No to question 2 were also presented with question 6 next, skipping questions 3, 4 and 5.

Results and Discussion

As shown in Figure 6, responses to question 1 indicated that only 25% of responding educators are familiar with using video modeling as an intervention to support children with special needs in their classrooms.

Q1: Are you familiar with using Video Modeling Interventions in the classroom?

Answered: 44 Skipped: 0

Answer Choices	Responses	
Yes	25.00%	11
No	75.00%	33
Total		44

Source: SurveyMonkey.com survey results

Figure 6 Survey question 1, are you familiar with video modeling?

Based on the responses to the first question, questions 2 through 5 were presented only to the 11 responders who indicated familiarity with using video modeling in the classroom. Figure 7 through Figure 10 present the responses to those questions. For question 2, only one responder indicated they use video modeling in the classroom. The responder answered by choosing the multiple-choice answer “Yes, for special needs students” and elaborated by choosing the “other” checkbox and entering “Yes, but I am cautious of over use. I use for all types of learners”. Two

other teachers indicated they may use video modeling in the future answering “No, but I would like to learn more about it and start trying it”, and “I haven’t used them this year, but I will consider using them”.

Question 3 was only presented to responders who answered Yes to question 2. The goal of this question was to probe for the teachers’ perspective on the human factors involved in using video modeling technology. In response to this question, the single teacher who provided a response indicated that he or she believe their current process for video modeling is indeed efficient.

Q2: Are you using Video Modeling in the classroom?

Answered: 11 Skipped: 33

Answer Choices	Responses	
Yes, for special needs students	9.09%	1
Yes, for typically developing students	0.00%	0
No	45.45%	5
No, I would like to but it is too difficult	0.00%	0
Other (please specify)	54.55%	6
Total Respondents: 11		

Source: SurveyMonkey.com survey results
 Figure 7 Survey question 2, do you use video modeling?

Q3: Do you consider your current process for video modeling in the classroom efficient?

Answered: 1 Skipped: 43

Answer Choices	Responses
Yes	100.00% 1
No	0.00% 0
Other (please specify)	0.00% 0
Total	1

Source: SurveyMonkey.com survey results
Figure 8 Survey question 3, is your process efficient?

Q4: What do you like the most about using Video Modeling in the classroom?

Answered: 1 Skipped: 43

Answer Choices	Responses
Efficient	100.00% 1
Analytics and Reports	0.00% 0
Ability to Validate Results	0.00% 0
Sharing with Parents	0.00% 0
Ease of Use	100.00% 1
Nothing	0.00% 0
Other (please specify)	0.00% 0
Total Respondents: 1	

Source: SurveyMonkey.com survey results
Figure 9 Survey question 4, what do you like the most about using video modeling?

Questions 4 and 5 also had a single responder each. Question 4 presented checkbox choices allowing for more than a single choice. The teacher indicted ease of use and efficiency as the factors they like the most about using video modeling. For question 5, the teacher indicated there is nothing they disliked about their current process for video modeling.

Q5: What do you like the least about Video Modeling in the classroom?

Answered: 1 Skipped: 43

Answer Choices	Responses
Inefficient	0.00% 0
No Analytics and Reports	0.00% 0
Inability to Validate Results	0.00% 0
No Sharing with Parents	0.00% 0
Difficult to Use	0.00% 0
Nothing	100.00% 1
Other (please specify)	0.00% 0
Total Respondents: 1	

Source: SurveyMonkey.com survey results

Figure 10 Survey question 5, what do you like the least about using video modeling?

Q6: Are you using apps for any purpose other than Video Modeling in your classroom, e.g. track behavior, track data, ...?

Answered: 40 Skipped: 4

Answer Choices	Responses	
Yes	42.50%	17
No	57.50%	23
Total		40

Source: SurveyMonkey.com survey results
 Figure 11 Survey question 6, are you using other apps?

Q7: What do you like the most about using the other apps in your classroom?

Answered: 15 Skipped: 29

Answer Choices	Responses	
Efficient	46.67%	7
Analytics and Reports	53.33%	8
Sharing with Parents	60.00%	9
Ease of Use	73.33%	11
Nothing	0.00%	0
Other (please specify)	6.67%	1
Total Respondents: 15		

Source: SurveyMonkey.com survey results
 Figure 12 Survey question 7, what do you like most about the apps you use?

Q8: What do you like the least about using other apps in the classroom?

Answered: 13 Skipped: 31

Answer Choices	Responses	
Difficult to use	23.08%	3
Inefficient	0.00%	0
No Analytics and Reports	23.08%	3
No Sharing with Parents	7.69%	1
Nothing	30.77%	4
Other (please specify)	15.38%	2
Total Respondents: 13		

Source: SurveyMonkey.com survey results

Figure 13 Survey question 8, what do you like the least about your apps?

Question 6 asked the teacher if they use other applications in their classroom for tracking behaviors, data, etc. As shown in Figure 11, 17 out of 40 respondents to this question indicated that they do use apps in their classrooms for tracking behaviors and data. The question specified tracking apps to exclude positive responses from teachers that merely used technology to teach material in their classrooms.

Questions 7 (Figure 12) and 8 (Figure 13) probed for the teachers' perspective on the human factors involved in using those apps. Both questions were checkbox, multiple choice questions, allowing for more than a single answer per responder. Ease of use was the most important human factor in using tracking apps in the classroom, coming in at 73.33% of the

responses. Ability to share data with parents come in second at 60%. Analytics and reporting also scored better than 50% at 53.33% while Efficiency came in at 46.67%.

While most responders had favorable opinions of the apps they use, difficulty of use and lack of analytics and reporting were the two items they disliked the most about their apps, though that percentage was still at 23%. For question 8 there were two “Other” responses from two different responders. They elaborated with “Bound to technology” and “There are some glitches with the program when inputting data and it is time consuming”.

CHAPTER FIVE: THE AIX FRAMEWORK

Overview

We introduce an emerging technology framework for longitudinal tracking of interventions, such as video modeling interventions, and token-based response cost interventions, in classrooms for students with special needs. The Applied Interventions for eXceptional-needs (AIX) technology framework is created to support special needs educators, therapists and caregivers in standardizing tracking and analysis of interventions. Informed by Applied Behavioral Analysis, the framework is technological, systematic, applicable at an early age, involves the parents, and can be applied at home. The goal is to provide teachers with tools that allow them to focus on the students instead of the implementation details of interventions, provide ability to track iterative interventions, provide analytical feedback to teachers, involve the parents and allow for augmented interventions at home and in clinics. The overall architecture of the framework is shown in Figure 14.

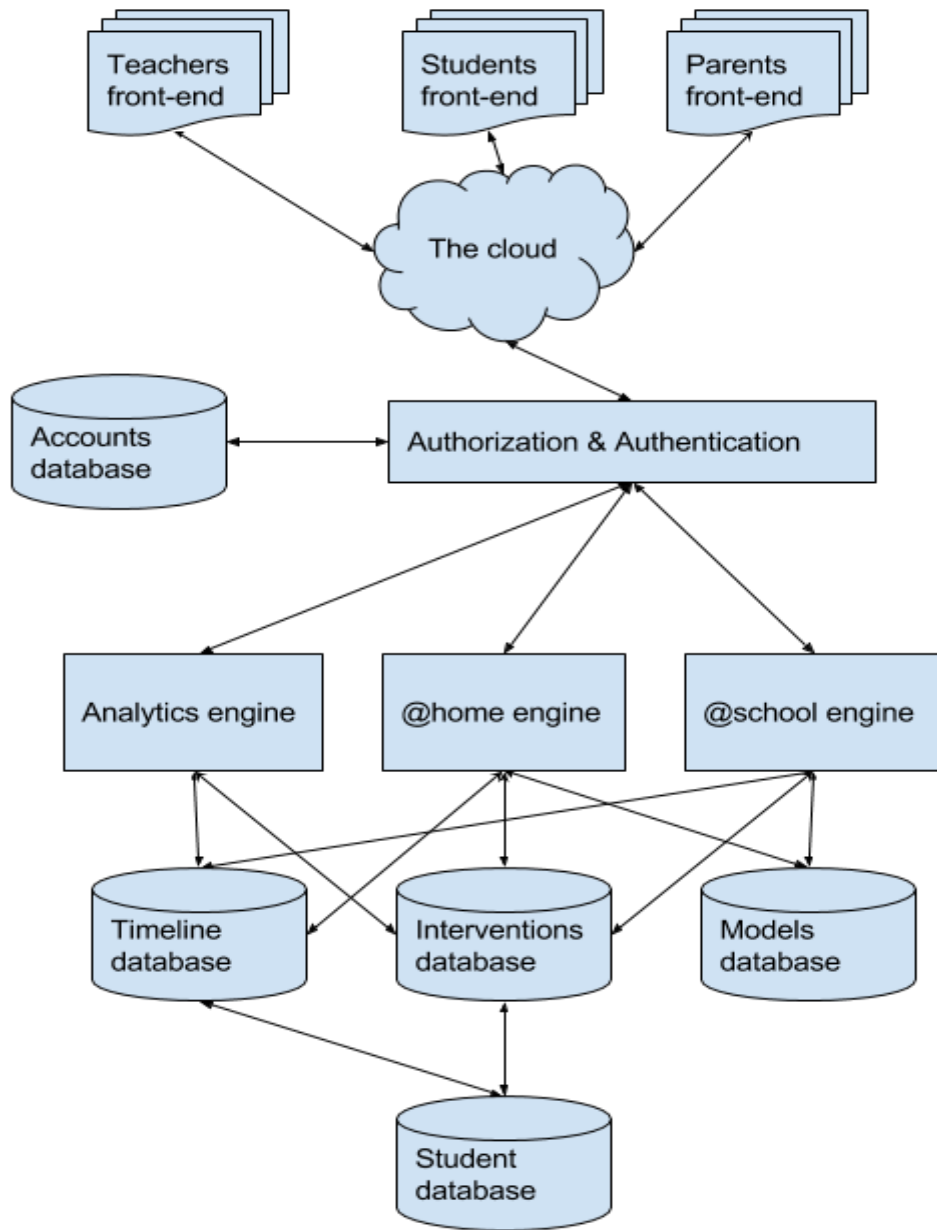
The foundation of this framework is a longitudinal student database. Current approaches to classrooms interventions are mostly based on teachers' ad-hoc planning, with results tracked using individual education plans (IEP) and individual behavior plans. While it varies between school districts, those approaches, for the most part, track target achievements but not intervention details. Prior plans are often referenced just as starting points; for example, if the goal is to reduce a child's stemming by 10% during a calendar year, the prior year is referenced just to get a starting point of the number of daily stemming events and not to correlate specific interventions and results from past years to the current year. In contrast, in the AIX framework, data is stored in the student database across years and across classrooms. The AIX framework is novel in two important manners. Firstly, in the AIX framework all data is owned by the student

and their caregiver, they are the ones that allow temporary access to teachers to the database, not the other way around. Secondly, the AIX framework tracks data longitudinally across years and classrooms.

On top of the students' database sits the interventions database. This is a database that tracks all applied interventions across time, environment and professionals. For example, a child having a video model intervention plan being applied over a semester at school, and a separate speech therapy intervention administered at a speech clinic would have both interventions tracked in this database. If the following year, the student gets another round of speech interventions administered at a different clinic, it too would be tracked in the same interventions database. Central to the framework is the timeline database, modeled after common social media applications, such as Facebook. The timeline contains activities, notes, achievements and context. The data is entered into the system by the teachers, the student, parents, therapists or caregivers.

Essential to the concept of video modeling discussed earlier is the ability to play a video model for the students when trying to teach them a new skill or to teach them to control an interfering behavior. As noted earlier in the 10 steps presented by Ogilvie (2011) and the nine steps presented by Indiana University Bloomington (n.d.), current approaches to implementing video modeling in practice require teachers to curate those video models. Our framework removes this barrier to utilization by including a database of video models grouped by purpose and age group. The framework allows teachers to share video models they produce or even allows outside professionals to produce video models and upload them to the system. The models database thus holds video models generated by the teachers as well as contributed by external professionals, with proper consent. When a teacher with limited technical resources, or

time, needs to apply a video model intervention to teach a student a new skill, she can refer to the model library to find a relevant video instead of trying to create one herself. Self-video models present a slightly different challenge. While clearly, they need to be of the student performing the skill, they can still be produced once, whether by the teacher, or the parents, and shared by the different parties applying the interventions. For example, an intervention augmented at home by the parents can utilize the same video model created at school by the teachers, or vice versa.



Source: image by author

Figure 14 AIX Architecture. Comprised of four databases, three engines, three front ends and an authorization & authentication layer.

Three software engines manage the interaction between the databases and the end users. The @school engine allows teachers to track interventions at the school. This engine allows a teacher to group students by class, creating a virtual class if they chose, that may match a physical classroom, be a subset of a physical classroom, or group students from several physical classrooms. This allows a teacher to track and administer interventions to multiple distinct students with ease through the same user interface. It is important to note here that the teacher would add an existing student to a virtual class but not create a new student record. This is important as we maintain that the student record is a longitudinal record that persists across years, classrooms, and schools. The @home engine allows parents, or caretakers, to create records in the system for their children, to authorize teachers and other therapists access to the children records for tracking interventions, to view intervention results, and to track interventions administered at home. Central to this framework is the concept of one record per child across their school career. Thus, it is important that a parent creates the child record and authorizes teachers and therapists access to the record. This access can be temporary, to match a therapy plan for example, and can be revoked any time by the parents, when the student changes schools for example.

At the heart of the work done by Baer, Wolf and Risley (1968) is emphasizing the analytical nature of Applied Behavioral Analysis. It is the author's experience that many special needs educators spend a disproportionate amount of school time collecting data, mostly via homegrown manual processes, often via pen and paper. The collected data is mostly used in individual education and behavior plans, and for explaining students' progress, or lack thereof. It is seldom the case that the data collected is used for analytical purposes relating methodology of

interventions to results. Even in the cases when classroom teachers have the capacity to analyze intervention methods and the resulting changes, the analysis is done in isolation of other classrooms, of prior years, and of any independent interventions conducted at home or in therapy clinics. There exists no standardized method for collecting and analyzing data across classrooms, teachers and years, that we know of. The analytics engine in the AIX framework aims to close that gap. The analytics engine operates on all data collected through the framework, whether at school, home, or therapy clinics, across all years of available data. There are three main functionalities for the analytics engine: a) efficacy validation, b) trend analysis, and c) correlation analysis. Special needs educators and parents know that effecting change, whether in behavior or in acquiring skills, is a long process, fraught with challenges and setbacks and ups and downs. What works for one student may not work for others, what works for one teacher may not work for others. The analytics engine provides feedback on efficacy of applied intervention to allow the teachers to decide on whether to proceed with, alter, or stop, a given intervention. While this process of validating efficacy of interventions is not new in classrooms for students with special needs, providing a framework and set of tools would make it easier for special needs teachers to utilize. Trend analysis provides concrete data for tracking skill acquisition, or regression, and behavior changes over long periods of time. The implications for trend analysis maybe apparent in neurotypical classrooms but are subtler in special needs environments. For example, boys with Fragile X, a genetic disorder that is the most common genetic cause of intellectual disability (Crawford, Acuna, and Sherman, 2001), are known to regress cognitively as they age (Hahn, Warren, and Fleming 2015). Dyer-Friedman et al. (2002) found that the quality of the home environment contributes to the variability of cognitive outcomes in boys with Fragile X. Hahn, Warren, and Fleming (2015) conducted a longitudinal

study on 55 children with Fragile X between the ages of 2, at the time of the initial observation for the youngest participant, to the age of 10 at the time of the last observation. In their study, they found that half the children showed true declines in one more adaptive behavior domains, the earliest age such declines in this population to have been documented. In their conclusions, Hahn, Warren, and Fleming posed an important research question: “can these declines in adaptive behavior be reversed or prevented?” and suggested annual assessments starting at an early age. The challenge with this requirement, which is not unique to children with Fragile X, is the difficulty of obtaining longitudinal data characterizing the natural history of students over long periods of time. Ability to conduct trend analysis and to correlate interventions to outcomes and results over long periods of time is one of the main reasons for creating the AIX framework.

The Authorization & Authentication layer provides for consent agreements and ensures proper access to records. Access is controlled by the caretaker, typically a parent, who creates the student record. This is in contrast with a new, but growing, segment of classroom management applications, such as the popular Class DoJo and Google Classroom, where the teachers are in charge of creating student records and granting access to parents. To further alleviate concerns of privacy, no privately identifying information (PII) should be stored in systems implemented based on the AIX framework.

There are three front-ends for this framework. A parent front-end that allows the parents to create a record, sans privately identifying information, for their child, assign access to teachers and therapists, and revoke access. The parents also get access to analytical dashboards as well as the ability to track at home interventions, view the timeline, including content added at school, and create video models. The teachers front end allows a teacher to create a virtual classroom

and to group students, as authorized by parents, into those classrooms, for tracking over a school year. The teachers front end also allows teachers to administer interventions, to track interventions, and to track behaviors targeted by the interventions. Finally, the students front end allows high functioning students to track some of their own data, for example tracking when they feel anxious or hyper. It also allows higher functioning students to administer some interventions on demand, for example viewing a video of a model behavior in a specific social setting.

Our expectation is that a discoverable, easy-to-use system, would increase the level of utilization of technology-based interventions in classrooms for students with special needs. To validate that assumption, we developed an easy-to-use, open source, mobile application based on the AIX framework that implements two interventions for reducing off task behaviors and teaching skills: i) Video modeling intervention, ii) Token-based response cost intervention. We sought four goals in building the system: i) ease of use, procurement and training was the main goal when designing the system. ii) implementation of an intervention that is familiar to teachers, specifically a token-based response cost procedure that is already used by many special needs teachers, though in manual fashion. iii) off-loading some of the tasks that the teachers conduct in their classrooms to the app such that the app reduces the workload on the teacher and does not increase it. iv) discoverable through app stores and sites dedicated to curating apps designed for students with special needs, allowing teachers to discover the app even if they are not familiar with the scientific research that lead to its development.

To achieve our first goal, we developed a responsive, html5, cloud-based app that requires no installation and works the same on smartphones, tablets and desktop computers. We modeled the app after familiar social media applications, such as Facebook, leading to minimal training requirements for using the app. For our second goal, the app implements a token-based

response cost intervention procedure. Specifically, when a student exhibits an off-task behavior, the teacher adds an entry in the student's timeline indicating the off-task behavior and any optional notes and context. The app keeps track of the time of the event and the number of off-task behaviors for each student.

Figure 15 shows the input screen when tracking a note, an activity, or an off-task behavior. The system defaults to the current time, but the user can override this, in case they are inputting data after the fact, for example if the teacher was monitoring children during recess and couldn't record a behavior until after they got back into the classroom. The activity field presents a drop down of activities relevant to the teacher, while the "what is happening?" field is a free text entry field. The mood icon indicates the mood of the student at the time of the activity. Finally, the teacher can note one or more interfering behaviors. Flagging any notable behavior with a thumb down to indicate an interfering behavior, or a thumb up to indicate the behavior was proper. Some teachers may choose to only track interfering behaviors, some teachers may choose to only track positive behaviors, or reduced interfering behaviors, and some teachers may choose to track both. At this time, the application is hard coded to the list of behaviors used in this study: hyper activity, proper eating, fast speech and giggly laughter.

The app displays a visual model representing the number of off-task behaviors for the day; the model is comprised of a bold red thumb down icon for each occurrence of an off-task behavior for the day. Thus, the first off-task behavior would be represented with one thumbs down icon. Five off-task behaviors in a day would be represented by five thumbs down icons.

Figure 16 shows the visual model for two off-task behaviors. Clicking the number in the app would read the count out loud to reinforce the visual model. Our third goal is focused on the teacher's already busy daily routine. Special needs teachers are often overworked and under-

supported, adding to their daily workload would lead to teachers not adopting any new system. Thus, the app allows the teachers to automate some of the tasks they already conduct in their daily routine. The app allows the system to track off-task behaviors with just a few clicks, keeping track of the time and frequency of occurrences, while providing daily, weekly and monthly rollup reports. The tracking and reporting, automate tasks that teachers already had to conduct, reducing their workload. The app also allows teachers to communicate with parents via the same timeline. The parents can post events to the timeline, for example, the student had a healthy breakfast today, and can view entries made by the teacher. The timeline interface, that many parents, students, and teachers are familiar with, through using social media apps, makes it easy for all parties to use the app to communicate on daily or weekly frequency, reducing the teacher's workload.

Time

10:42 PM

Activity

Social Studies

what is happening?

This is a sample post.

Mood



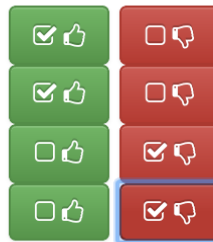
Behavior

Hyper Activity

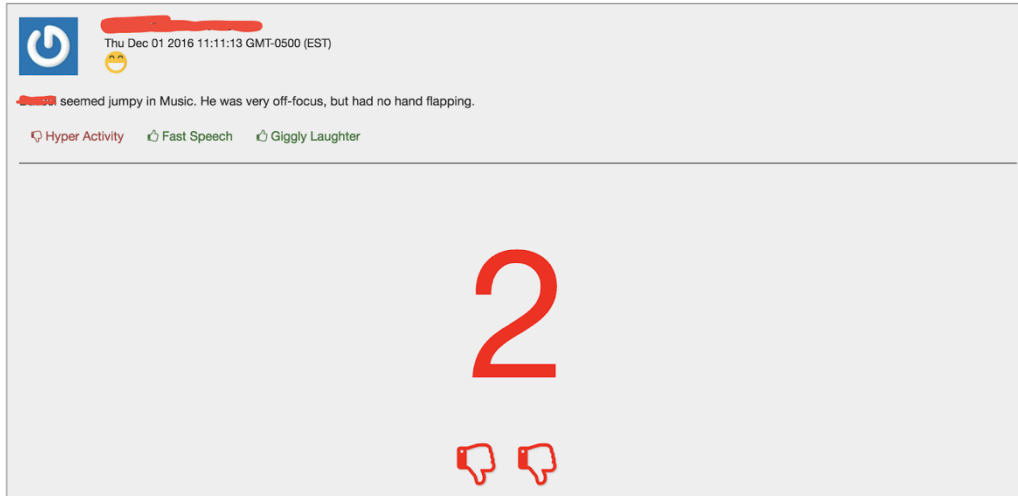
Proper Eating

Fast Speech

Giggly Laughter



Source: image by author
Figure 15 Using the app to track behaviors.



Source: image by author
Figure 16 Visual Model Intervention.

To validate the assumption that an easy-to-use app would be utilized by special needs teachers we conducted a 16-week, A-B-A case design, pilot case study. The case study had a single participant, a special needs teacher, certified in Applied Behavior Analysis, who used the app to apply and track interventions for one male student, with Fragile X syndrome who exhibits frequent off-task behaviors that interfere with his ability to learn as well as hinders his social interactions with his peers. The student and his teacher are part of a private school for students with special needs that focuses on Applied Behavioral Analysis. All students in the school are students with special needs with cognitive challenges and autistic behaviors.

We conducted the pilot case study in the small private school for students with special needs. The student's classroom has eight total students, a primary teacher, who was our study participant, a full-time teacher assistant and an assistant who splits his time between several classrooms. The student is pulled out for basic math once a day, but otherwise spends the day with the same group of students, while supervised by the same group of teachers. The students learn basic skills, eat snacks and lunch, participate in PE, watch videos, as well as receive basic

reading, writing and math tutoring. In the study, the teacher tracked four off-task behaviors that the student exhibited for all his school career. The behaviors, unrelated to this pilot study, were written in the student's IEP plan. Reducing the behaviors was a goal of the parents and teachers for multiple years. The goal of the study was to understand the teacher's inclination to utilizing a mobile app to apply and track interventions. Since this was a long-term study, set in a natural setting, there were no external independent observers.

The teacher spent a week learning the app and practicing data entry. The study then commenced with a baseline phase of three weeks, during which baseline observational data were collected. Following the initial three weeks, there was a two-week period of applying token-based response cost interventions using visual models followed by another two-week period of applying the token-based response cost interventions using visual models as in the first two weeks, plus showing the child a self-video-model of the desired replacement behavior. After a week break due to the Thanksgiving holiday, the research began the final phase, the maintenance phase. The maintenance phase included three weeks of data collection, followed by three weeks of break due to the winter holidays and finally concluded with two weeks of data collection at the onset of the new semester.

During the baseline phase the teacher tracked behaviors using the Interval Recording technique utilizing 30-minute intervals. The teacher marked thumbs up or thumbs down for each of the four tracked behaviors corresponding to the interfering behaviors exhibited by the child:

1. Hyperkinesis
2. Fast unintelligible speech
3. Uncontrollable laughter
4. Messy eating

The student was in the presence of at least two teachers at most times. When two or three teachers were present they consulted on coding the behaviors and tracked a behavior only if all present teachers agreed. Infrequently, such as during recess, the child was in the presence of one teacher, in which case the teacher was the single observer tracking the behavior. In a post study interview we asked the primary teacher how inter-observer disagreements were handled and the response was: “The specific behaviors we are tracking are so intense and obvious for this child we had no disagreements on coding them.” The teacher’s description of the behaviors matches the parents’ description as well as what is usually described in literature.

The teacher also noted the activity the child was engaged in, e.g. Lunch, Snack, Reading, Math, ..., as well as general notes. Prior to commencing the study the teacher had been using a strategy of naming interfering behaviors as red thoughts and presenting students with a thumb down hand gesture. The teacher presented proper replacement behaviors as green thoughts and displayed a thumb up gesture using her hands.

The primary teacher continued her classroom practice of noting children’s behaviors and alerting them to “red thoughts” as well as offering them replacement behaviors. During the first two weeks of applying visual interventions the teacher would alert the child to the “red thought” as usual, offering him the replacement behavior, and additionally showing the child the number of red thoughts on the smartphone app in a large red font. The app also displayed a series of red thumb down icons corresponding to the number of red thoughts accumulated for the day. Collectively the display of the large red number as well as the thumbs down icon is what is referred to as the Visual Model in this part of the study.

For illustration purposes, if the child had an episode of hyperkinesis, the teacher would mark a red thought on the smartphone app, then alert the child to his behavior and show him the phone's screen with a large number one on the screen and a single red thumb down icon. If the child then had an episode of messy eating during that same school day then the teacher would mark another red thought on the app, alert the child to his behavior, offer a replacement behavior, and show him the phone's screen with a large number two on the screen and two red thumb down icons.

During the next two weeks of interventions the teacher followed the exact same procedure listed above but additionally played a short previously-recorded video of the child behaving properly. The study used two video self-models. The first was of the child eating without making a mess. The second was of the child drawing calmly with pencil and paper and properly answering simple questions about his activity without speaking too fast. The first video was used in interventions targeted at messy eating. The second video was used for the other three interfering behaviors.

During the four weeks of intervention the teacher also used the app to record the child's response to the intervention. The teacher recorded one of four possible responses:

1. The child stopped the interfering behavior immediately
2. The child continued the interfering behavior as he used to prior to the intervention
3. The behavior lasted for a shorter period than typical of the child
4. The behavior intensified and lasted for a longer period than typical of the child

During the maintenance phase, the teacher tracked the child's behaviors using our smartphone app, but without using the smartphone app to apply interventions. The teacher

continued to conduct the classroom in typical fashion alerting the students, including our student, to interfering behaviors and offering antecedent-based replacement behaviors.

Results

The formative pilot case study ran for 29 calendar weeks. After the initially planned 16-week pilot case study the teacher requested to continue using the software through the end of the school year for tracking interventions, leading to 29 weeks in total usage, for which we collected data throughout. The study started in the middle of the first semester and ran through the end of the school year. This period spanned school holidays, sick days, and field trips. In total, the teacher recorded a 1974 data points, including observations of interfering behaviors, positive behaviors, notable activities, and notes, applying interventions and tracking responses. On average, 68 data points were collected each week. The system allows the user to note multiple data points for each timeline entry. For example, while noting a child's activity, the system can also record the child's mood and the status of tracked behaviors, all in a single timeline entry. In all, the system contained 490 timeline entries over the trial period, averaging just under 17 entries per school week, or around 3.4 timeline entries per school day. Table 13 shows the progress of recording the interfering behaviors for the child during the 16-week pilot study. The interfering behaviors were coded by the teacher and not an independent observer. The teacher recorded the type of interfering behavior as listed in columns 3,4,5, and 6 in the table. Table 14 lists the average of all those behaviors in every school day. The child did not make it to school every day, because school was off, he was sick, it was a field trip day, etc.; thus the table shows the actual count of attended school days per week and the average count of interfering behaviors, across all four behaviors per day.

Table 13 Number of Interfering Behaviors Recorded Per Week

Phase	Week	Hyperkineses	Laughter	Eating	Speech	Total
Baseline	1	4	2	2	4	12
Baseline	2	9	3	3	5	20
Baseline	3	2	2	4	2	10
Intervention	4	2	2	5	1	10
Intervention	5	0	2	0	3	5
Intervention	6	1	0	2	0	3
Intervention	7	0	0	0	1	1
Break	8	0	0	0	0	0
Maintenance	9	2	0	1	2	0
Maintenance	10	0	0	0	0	0
Maintenance	11	0	0	0	0	0
Maintenance	12	1	0	0	1	2
Break	13	0	0	0	0	0
Break	14	0	0	0	0	0
Maintenance	15	1	0	0	0	1
Maintenance	16	2	0	0	0	2

Table 14 Daily Average of Recorded Interfering Behaviors.

Phase	Week	School Days	Average Interfering Behaviors
Baseline	1	3	4
Baseline	2	5	4
Baseline	3	5	2
Intervention	4	5	2
Intervention	5	5	1
Intervention	6	5	0.6
Intervention	7	4	0.25
Break	8	0	0
Maintenance	9	5	1
Maintenance	10	2	0
Maintenance	11	3	0
Maintenance	12	4	0.5
Break	13	0	0
Break	14	0	0
Maintenance	15	5	0.6
Maintenance	16	5	0.4

CHAPTER SIX: THE LEXY FRAMEWORK

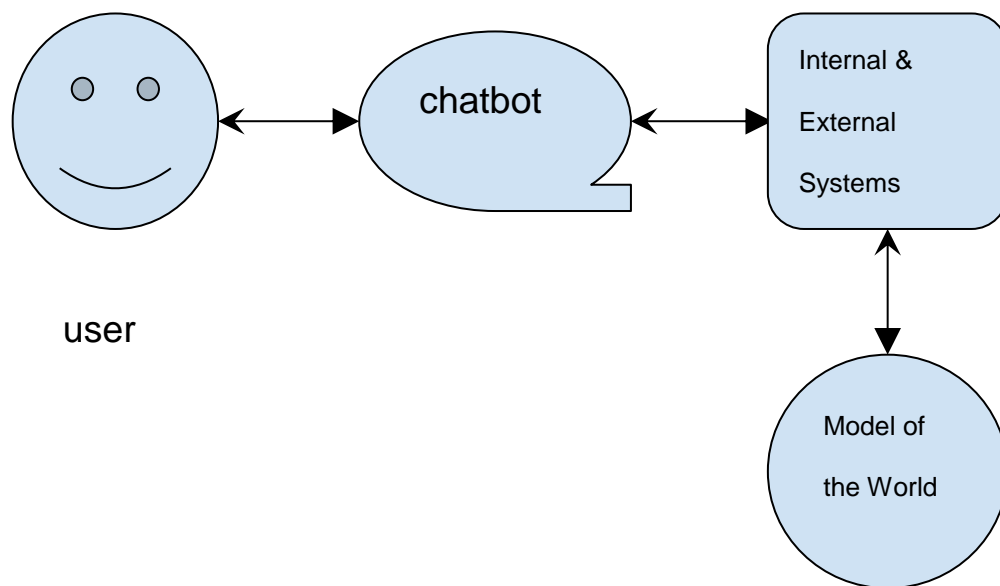
Overview

We introduce the Language Enhancements for eXceptional Youth (LEXY) framework, an emerging technology framework for developing conversational interfaces on top of the Amazon Lex and Amazon Polly services. In order to explain the novel contribution of the LEXY framework let us first consider the flow of a typical chatbot.

Figure 17 shows an illustrative, very simplified, flow of a typical chatbot where one user interacts with the chatbot. The chatbot's logic would interact with internal business logic and external systems, build a model of the world based on business logic and input from external systems, and interact with the end user accordingly. In contrast, Figure 18 highlights the distinction of the LEXY framework which adds interactions with other actors, for example a caregiver, to curate and augment the model of the world.

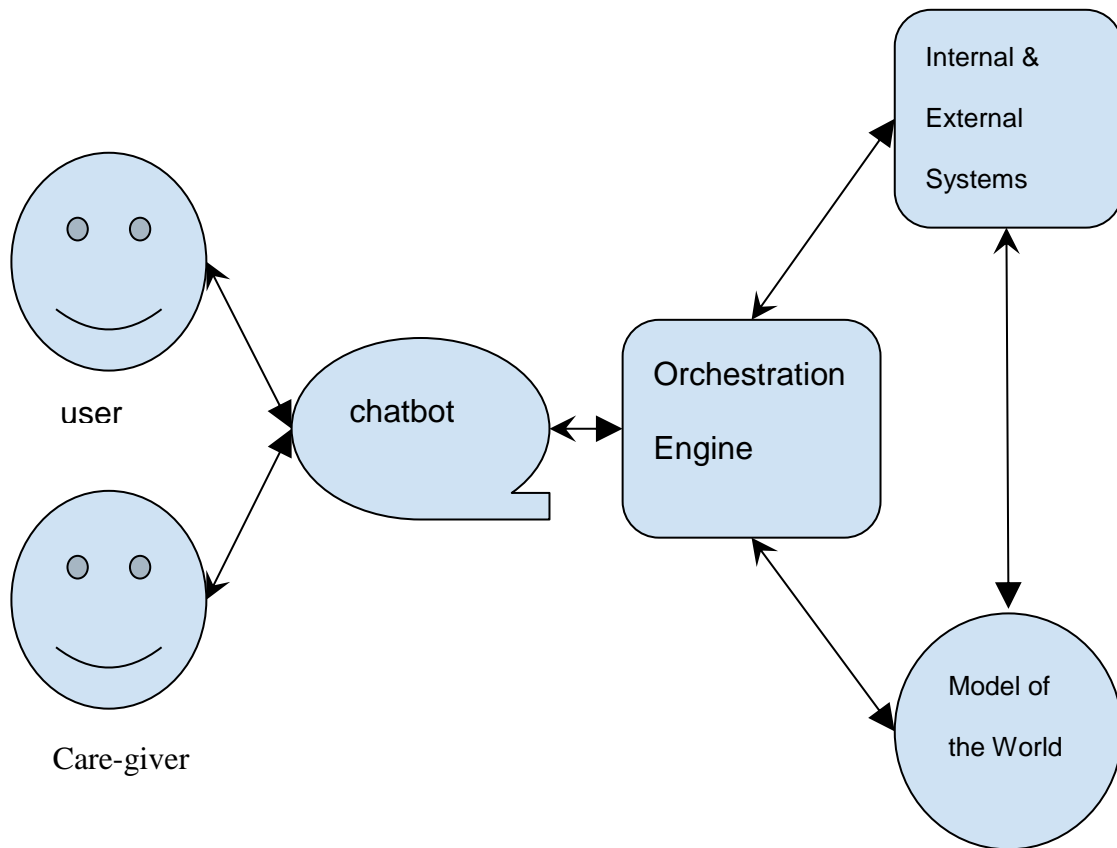
The current state of the art in conversational interfaces, whether at home such as Amazon Alexa, or in a business setting, such as customer service chatbots, is centered around the fulfillment of a single intent. An intent is the basic unit of work in conversational interfaces. An intent is modeled by a collection of utterances. Each utterance is composed of natural language words and slots. An example of an intent would be "order ice cream". Sample utterances to model the intent could be "I want ice cream", "I would like to order ice cream", "I want 3 scoops of ice cream", "I would like to order 2 scoops of chocolate ice cream". To allow for dynamic natural conversions, the last two utterances can be modeled with slots, or placeholders, representing the number of scoops and flavors as follows: "I want {count} scoops of ice cream" and "I would like to order {count} scoops of {flavor} ice cream". For the chatbot to fulfill the

intent it needs to resolve the two slots, {count} and {flavor}. If those slots are present in the conversational request, for example: “I would like to order 2 scoops of chocolate ice cream”, then the chatbot can fulfill the intent without further interaction. If on the other hand, the utterance was missing some of the information, for example, “I want ice cream” then the chatbot would prompt for the number of scoops and the desired flavor. For simplicity, we assume the intent is fulfilled once the bot infers the intent from the utterance. In real life scenarios, a further action, such as a person procuring the ice cream, would be the final step in the process.



Source: image by author

Figure 17 A simplified model of a typical chatbot interaction.



Source: image by author

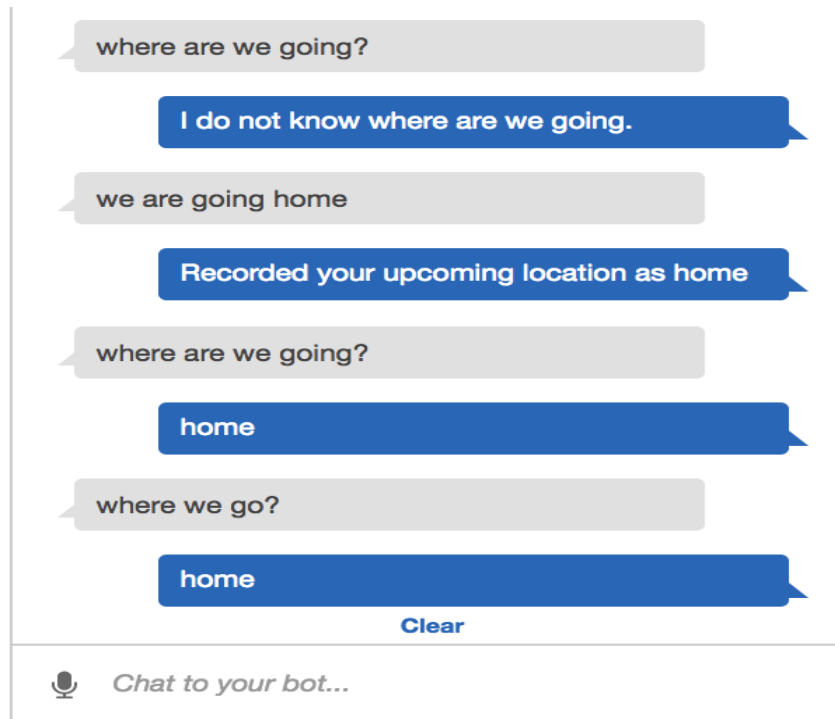
Figure 18 The LEXY Framework allows actors to curate the model of the world.

In order to provide an interaction that goes beyond fulfilling a simple intent, a chatbot must maintain context, session, a state machine and a model of the world. Systems such as Amazon Alexa have large teams of developers that build sophisticated business logic and leverage machine learning and external sources to build context and a model of the world allowing it to respond to requests. For example, if a user asks Alexa to “Alexa, add coffee to my shopping cart”, Alexa would already know the user from the account tied to the device, it would know their shopping history, allowing it to know what type and size of coffee to add, and would

have access to their shopping cart. Yet, at this time, Alexa cannot have a multi-turn conversation out of the box and is limited to fulfilling a single intent. The global Amazon Alexa competition offered a large prize for teams from universities around the globe to develop applications that can hold a natural conversation with Alexa. The winning team in 2017, after a year's worth of development, won by managing a 10-minute conversation (Amazon Developer, n.d.), highlighting the difficulty of developing a natural conversation system.

Our framework, being a purpose-specific framework does not attempt to handle generic requests but only to fulfil specific requests leveraging a model of the world created by interacting with a caregiver. The generality of the LEXY framework stems from the variations in the model of the world created by the caregiver but its specificity is derived from it being a purpose-specific framework that is meant to answer a specific set of requests. The goal of building the framework is to show that Amazon Lex and Amazon Polly can be used to model augmentative and assistive technology and that they can be used to develop conversational chatbots for supporting children with intellectual disabilities. In Figure 19 we present a simulated, sample, conversation between a prototype chatbot that implements the LEXY framework and two actors, a child with autism and a caregiver. In this conversation, the responses from the prototype chatbot are real while the input is provided by the author to simulate input from a care-giver and a child with autism, with the goal of illustrating the behavior of the chatbot as the conversation progresses. The conversation can be a spoken voice conversation, a typed text conversation, or a mixture of both. The illustrative conversation starts with the child asking “where are we going?”. The model of the world has not been seeded by the caregiver yet, so the chatbot does not know and it responds with “I do not know where we are going.”. The caregiver then tells the chatbot that “we are going home”. Subsequent questions by the child would then receive the correct

answer from the chatbot. The example in the figure shows the chatbot, recognizing different variations of the question, answering the question correctly and repeatedly. In this specific example, the second variation of the question, “where we go?” is not part of the chatbot configuration but was resolved correctly by Amazon Lex to match the intent “where are we going?”. Resolving unspecified utterances is an important component of the Amazon Lex service. Without this component, a person developing the chatbot in this example would have to specify all acceptable utterances, with the chatbot failing to respond to any utterances not explicitly specified by the developers. In this particular instance the prototype chatbot was built with the following three utterances: “where are we going”, “going where”, ”where”. From those utterances, Lex resolved the utterance “where we go?” to the intent attached to those three utterances. It is important to note that there are design trade-offs when deciding on what utterances are used to model an intent. The more flexible, less specific an utterance, the more likely Lex will match against the wrong intent in a chatbot that has multiple intents.



Source: image by author

Figure 19 A simulated conversation between a prototype chatbot and two actors, the child with autism and their caregiver.

The LEXY framework is composed of: 1) pre-configured intents, utterances and slots, 2) an orchestration engine, 3) a business logic engine, and 4) a set of purpose-specific finite state machines. The orchestration engine and the business logic engine are developed using AWS Lambda, a service for developing serverless cloud functions. The finite state machines are implemented using Lambda functions and DynamoDB, a NoSQL cloud database-as-a-service from AWS. The purpose-specific activities handled by the LEXY Framework are based on popular activity boards, based on the picture exchange communication systems, often used by occupational therapists and caregivers to aid children with autism (Dooley, Wilczenski, & Torem, 2001). The set of activities supported by the LEXY framework at this time are “First/Then”, “Schedule”, and “Coping”.

Figure 20 illustrates the general architecture of the LEXY framework. The same user interface is used to interact with end users, such as children with autism, and caregivers. The user interface can be a smartphone app, an Alexa device, a web application or other custom developed applications. All conversational interactions flow through the AWS Lex service along with LEXY's pre-configured utterances and slot types to resolve a user input utterance into an intent. Once an intent is resolved, the orchestration engine takes over to decide how to handle the intent by invoking the appropriate chatbot. Each chatbot would then apply its business logic to update the applicable state machine and the model of the world. The model of the world and state machines are available to all chatbots which is what allows LEXY to interact with multiple actors successfully. The system's state, composed of the model of the world, the state machines, and ancillary data, is saved to DynamoDB for persistence. The Orchestration engine, user chatbots, caregiver chatbots, model of the world, and state machines are developed using stateless cloud functions. Therefore, we need to persist the state of the cloud functions to a database. The state is hydrated from the database upon cold invokes of those cloud functions. Under the hood, AWS implements lambda functions as Docker containers that are disposed of after a period of inactivity, currently 15 minutes. If the system's load increases AWS would instantiate multiple copies of the Docker containers, each needing to hydrate its state from the NoSQL DynamoDB. For simplicity, we did not include the session management and user identification components in the diagram but those components are also part of the framework.

At this time, the LEXY framework supports the following activities: "First/Then", "Schedule", and "Coping". First/Then activity boards are typically structured around two activities, the sought activity and the required activity. For example, to watch TV you must first do homework. In a typical environment, the activity board would contain pairs of pictures of

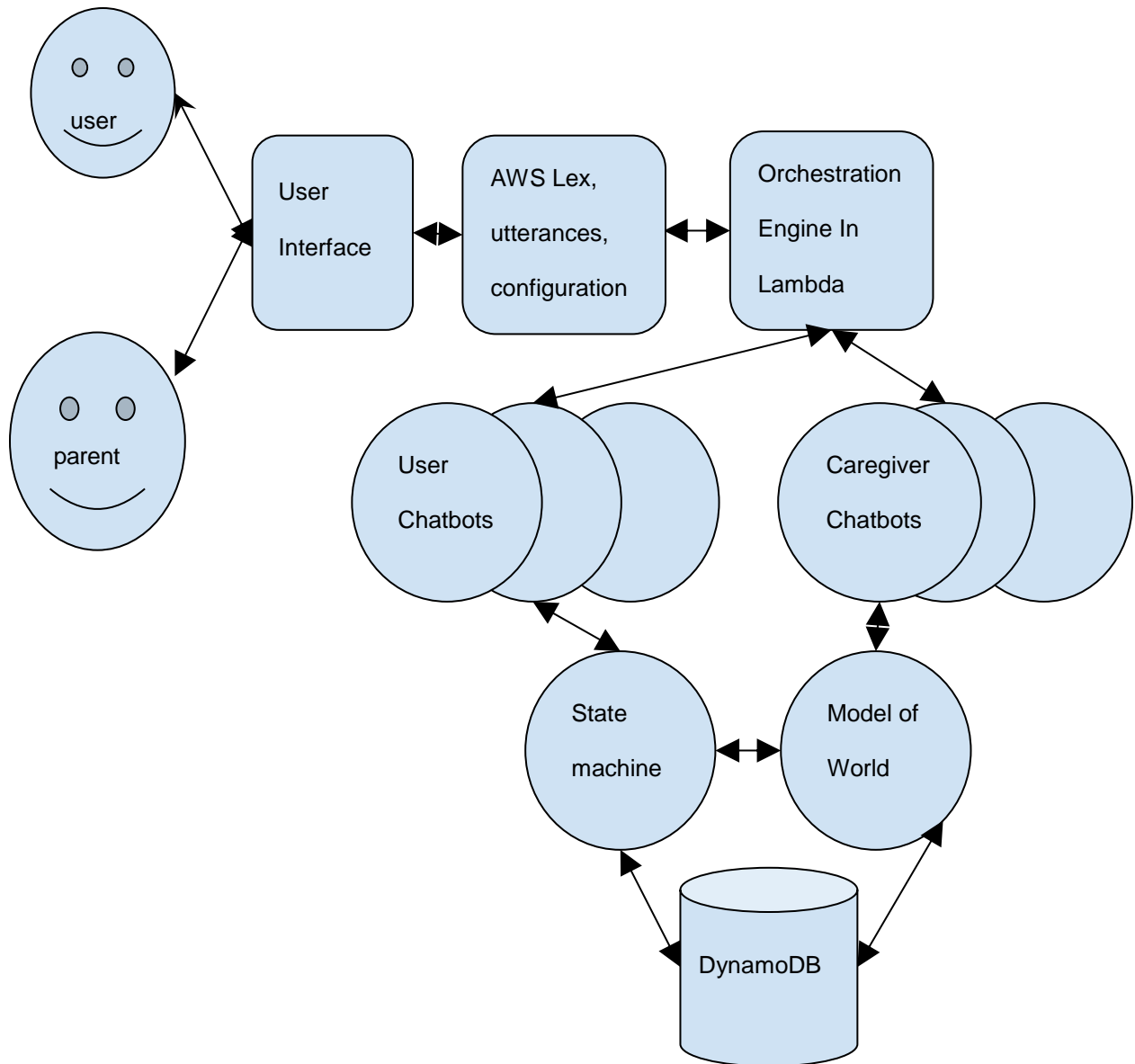
activities. For example, a picture of a TV next to a picture of a child studying. When the child requests to watch TV the caregiver would point to the activity board and reiterate that to watch TV the child must complete the required activity of doing homework. As these boards are typically physical boards with physical pictures on them, they are relatively easy-to-create at home by the caregiver but are static by nature and practicality limits them to a small set of activities. In LEXY, the “First/Then” activity is dynamic and is configured by the caregiver.

Schedule boards are used to list a sequence of events; they can be used to describe a daily schedule, for a specific complex task, or for a sequence of events within the day. A daily schedule board may have a picture of breakfast, a school bus, a classroom, a school bus and a home to indicate to the child they need to eat, go to school, spend the day at school and come back home. At school, another schedule board may contain a picture of books, lunchbox, playground and books again to indicate that the child will have some classroom time, then lunch time, then recess, and finally back to the classroom. In the LEXY framework, the schedule boards are an extension of the First/Then activity. The caregiver would conversationally specify to the chatbot what are the events, and their sequence, that comprise the schedule, the chatbot would correspondingly interact with the child informing her of the next activity when she asks. Both the child and the caregiver, or a teacher, can inform the chatbot of completed activities.

Coping boards are used to identify emotional state and present options for the child depending on their state of mind. For example, when a child is feeling anxious, a coping board can have picture options for “taking a deep breath”, “counting to 10”, or “go to a quiet place”. Coping boards are implemented in LEXY using the more general If/Then activity. The If/Then activity implements the inverse workflow of the First/Then activity. While in the First/Then activity the child seeks a desired outcome, in the If/Then activity, the triggered event, for

example feeling anxious, would trigger the outcome. Additionally, an If/Then activity can have multiple options, all of which are enumerated to the child when the child informs the chatbot of her state of mind. For example, if the child informs the chatbot that she is anxious, the chatbot would respond with something like: “If you are feeling anxious you can try taking a deep breath, counting to 10 or finding a quiet place for a few minutes.”

To validate the framework, we built a prototype chatbot that was tested using the AWS Lex testing interface. We then simulated the input from a child and a caregiver while the chatbot handled the resolution of intent, responses and fulfilling the intents. All interactions from the bot as presented in the result are actual interactions from our chatbot, while all human input is a simulation of what the child or the caregiver would say.

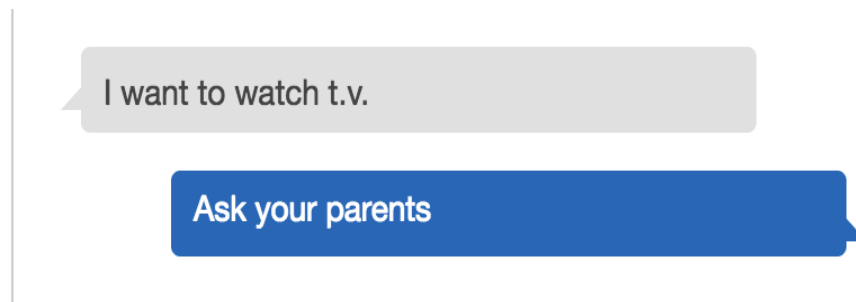


Source: image by author
 Figure 20 General Architecture of the LEXY Framework.

Results

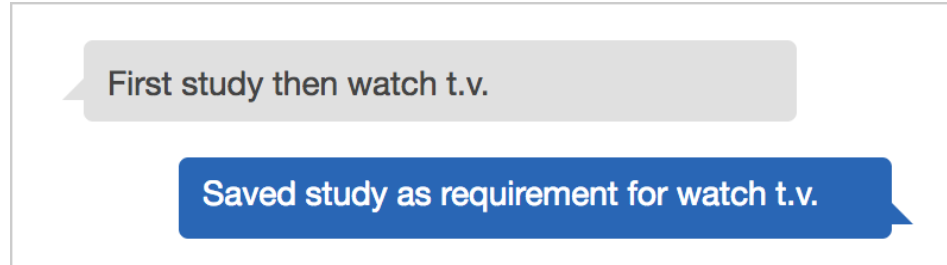
Simulation of Schedule Board Activity

Figures 21 through 24 show a typical interaction with the prototype chatbot for a First/Then activity. In Figure 21, the child asks the chatbot to watch TV. The chatbot, having not yet built a model of the world, is not aware of the requirements for watching TV and thus informs the child they need to ask their parents. In Figure 22, the parent builds the model of the world by telling the chatbot that study is a requirement for watching TV. In Figure 23, the child repeats the request. Since the model of the world has been built, the chatbot responds differently this time. Instead of asking the child to “Ask your parents”, this time the chatbot informs the child that the child needs to study first. The conversation concludes in Figure 24, when the child has completed studying and the chatbot responds appropriately informing the child that she can watch TV.



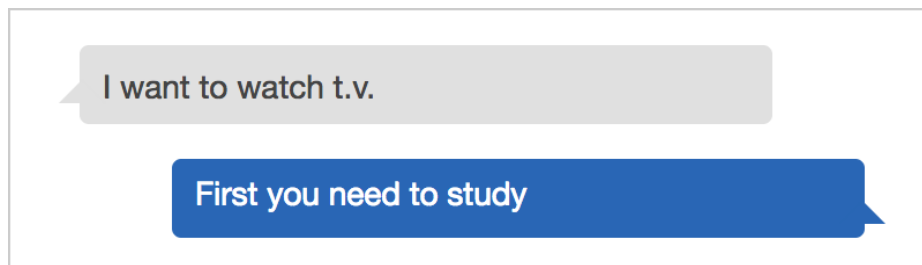
Source: image by author

Figure 21 The child informing the chatbot that the child wants to watch TV



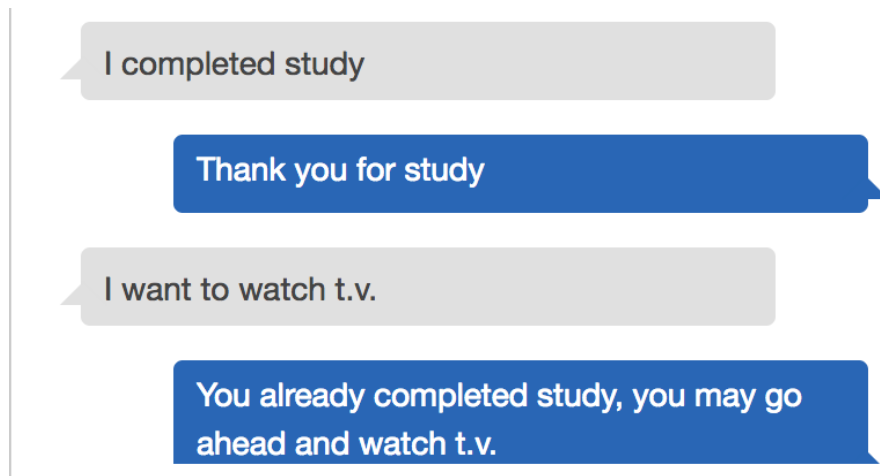
Source: image by author

Figure 22 The parent is building the model of the world conversationally.



Source: image by author

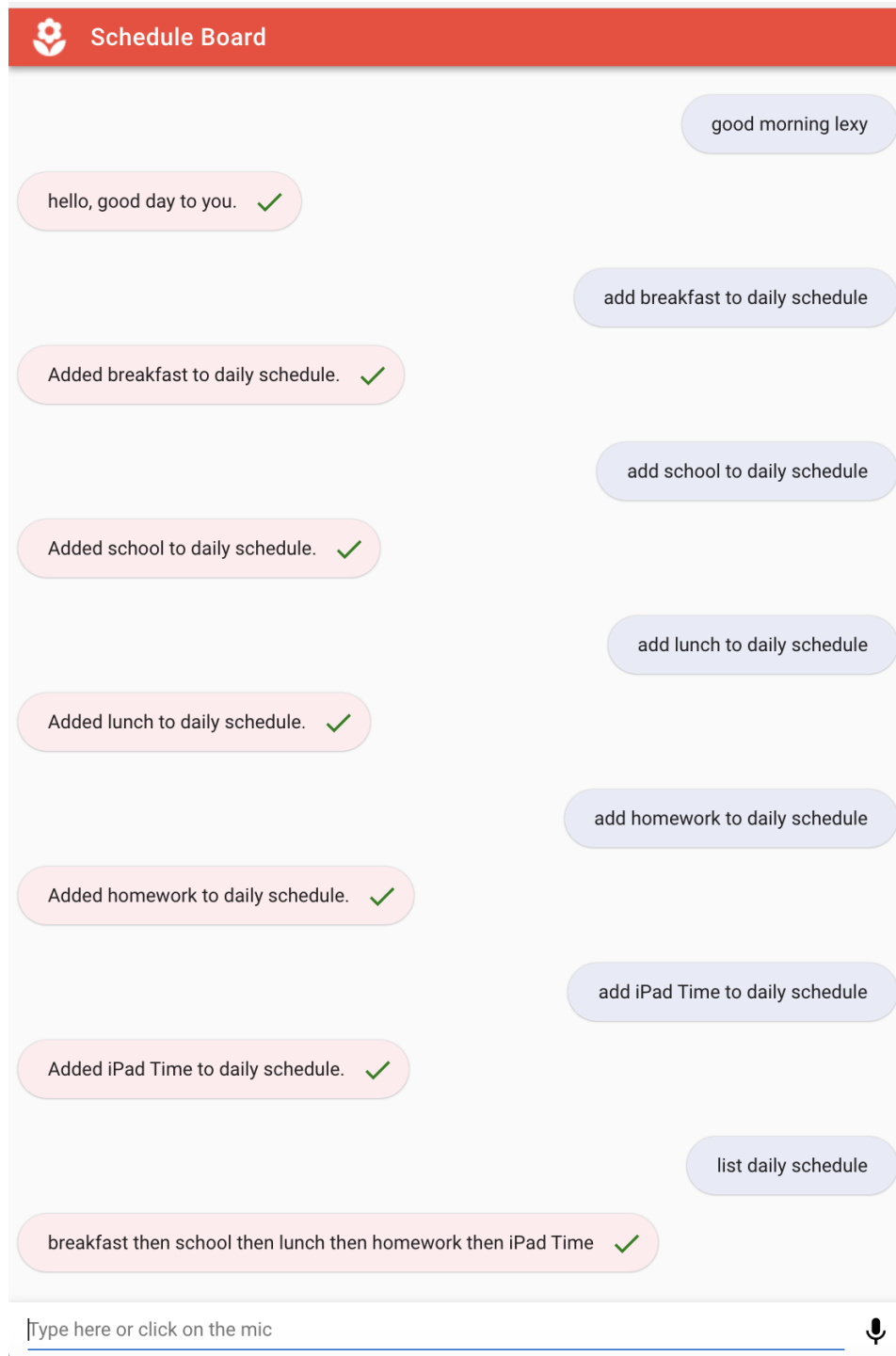
Figure 23 The child repeating the request, after the model of the world has been built.



Source: image by author

Figure 24 The child interacting with the chatbot after completing the required chore.

Simulation of Schedule Board Activity



Source: image by author

Figure 25 A parent using our prototype software to create a schedule.

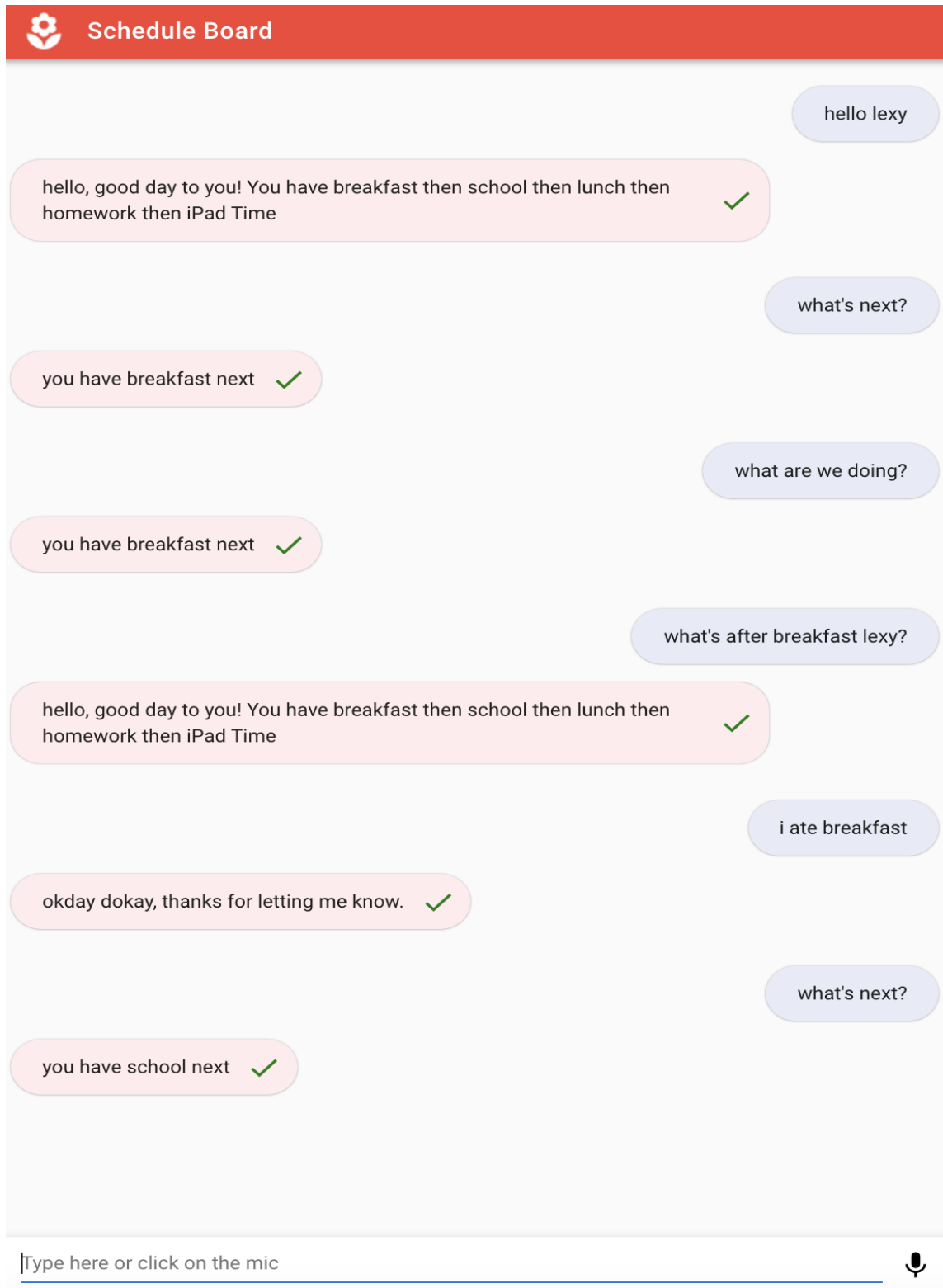
Figure 25 shows a screenshot of our prototype chatbot application conversing with a parent who is curating the model of the world. In this example, the parent is creating a daily schedule made up of breakfast then school then lunch then homework then iPad time. The conversation is conducted in text for the purpose of capturing screen shots, but the conversation could have been completely spoken with the exact same results. The text bubbles on the right-hand side, are those of the parent's side of the conversation. The responses on the left, having the pink background and the checkmarks, are the actual responses from the chatbot. The author simulated the role of the parent by asking the chatbot to create the schedule, but all interactions and responses are from the prototype chatbot and are not a simulation.

Figure 26 shows the conversation between the prototype chatbot and a child. The child's side of the conversation is simulated based on actual conversations the author's child has with him on daily basis. The chatbot's responses are real responses from the prototype chatbot and are not simulated.

Simulation of a Coping Board

The final simulation is of a coping board. Coping boards are used to support children with special needs to help them answer questions like "what do I do if I am feeling anxious?". This typically lists one or more options for self-aware children to engage in if they need to cope with a situation. For example, if a child is feeling anxious, they can look at their coping boards which can have options such as "take a deep breath", "find a quiet room", etc. Figure 27 shows a parent curating the model of the world for a coping board. The LEXY framework allows the caregiver to dynamically specify the situations and their options. Unlike a paper-based coping board that lists a limited set of options for a specific situation, with LEXY both the situations and

their options are not restricted by limited space. Naturally, the situations and options can be curated for the child's specific need and situation, and can be updated as context changes. Figure 28 shows a simulation of a child interacting with the chatbot after it has been curated. It shows the child prompting for two scenarios, being hungry and being anxious, and the chatbot responding with options that have been curated by the parent. If there is more than one option per scenario, the chatbot would return a random selection of the options. The chatbot would keep interacting with the child, no matter how many times the child repeats the question, a very common occurrence for children in our target population. Figure 29 shows a conversation between the chatbot and a child with special needs. The child's input is a simulation by the author based on a typical conversation. The chatbot responses are the true, non-simulated, responses of the chatbot. This figure demonstrates that the chatbot handles multiple scenarios, a daily schedule and a coping board simultaneously. A scenario not possible in paper-based schedules and boards.



Source: image by author

Figure 26 The prototype chatbot responding to a simulation of a child conversation.



Schedule Board

when feeling anxious you can take a break

when feeling anxious: take a break ✓

when feeling anxious you can count till 10

when feeling anxious: take a break or count till 10 ✓

when feeling anxious you can take 10 deep breaths

when feeling anxious: take a break or count till 10 or take 10 deep breaths ✓

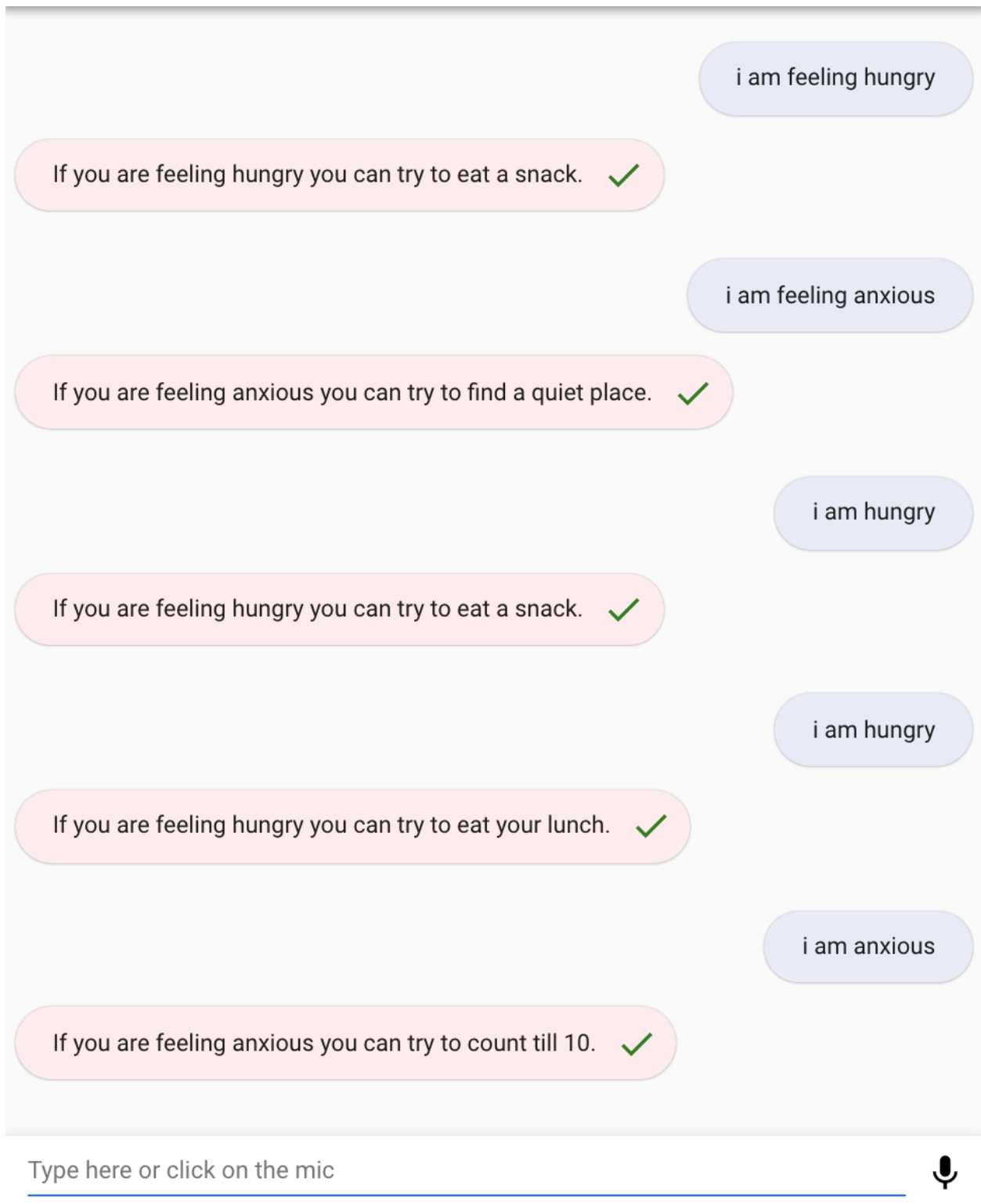
when feeling anxious you can find a quiet place

when feeling anxious: take a break or count till 10 or take 10 deep breaths or find a quiet place ✓

|Type here or click on the mic

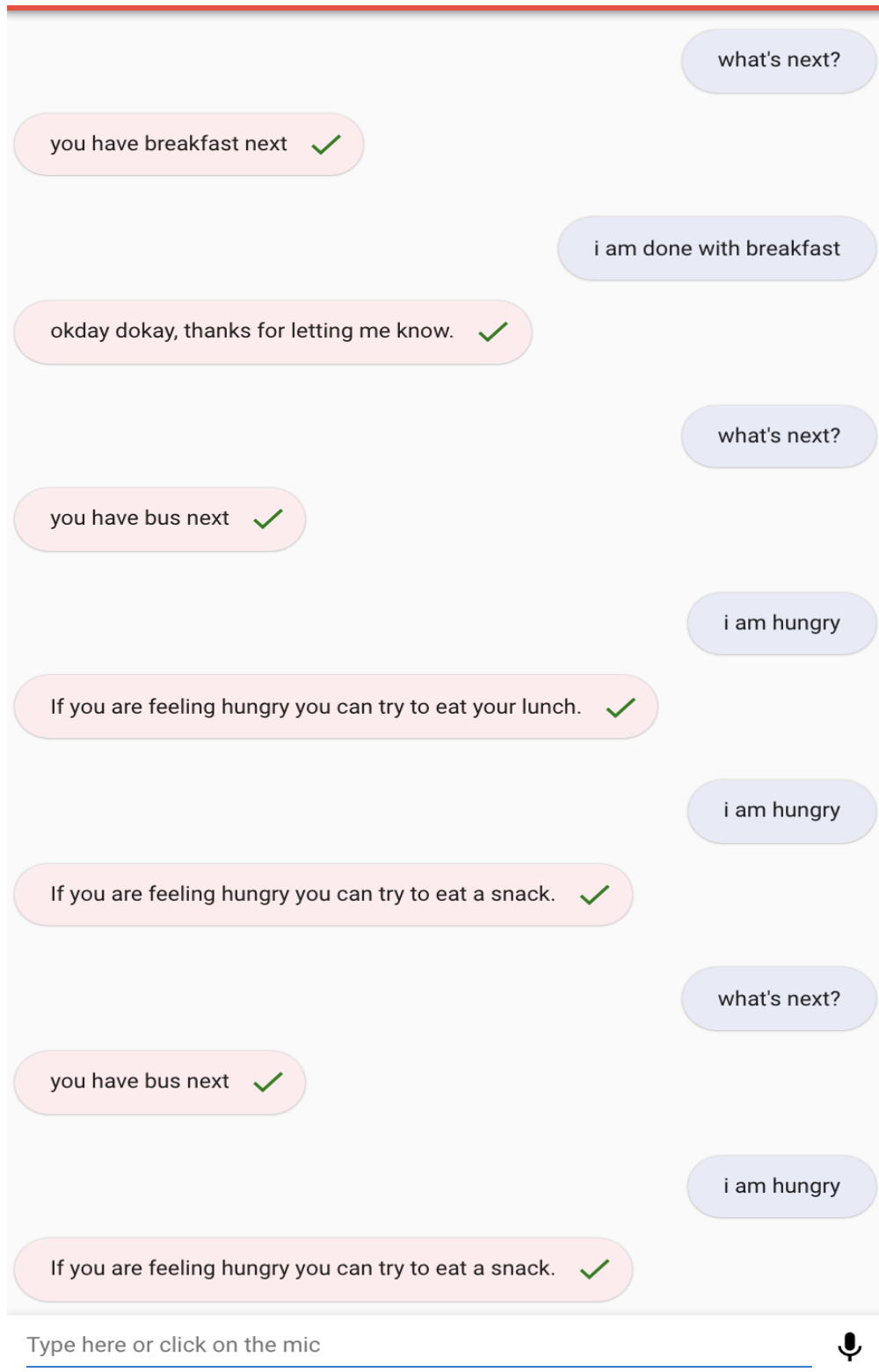


Source: image by author
Figure 27 A parent curating a coping board conversationally.



Source: image by author

Figure 28 A simulation of a child interacting with the chatbot when needing to cope.



Source: image by author
Figure 29 The chatbot handling multiple scenarios at once.

CHAPTER SEVEN: CONCLUSION AND FUTURE THOUGHTS

Analysis of Social Discourse Framework

Sample Language Analysis is an important tool for Speech-Language Pathologists to assess the language abilities of children and adults with speech and language impairments. While important, its utilization has been limited due to the following human factors: a) Manual analysis of samples is not efficient and can only examine 1 or 2 metrics., b) Computer-aided analysis requires commercial PC-based software that is dated, not readily available and is capped in terms of the metrics it provides. The actual process of speech capture also requires other devices such as voice recorders and transcription tools.

The current approach of obtaining language samples through direct interaction with the children can sometimes yield poor results due to the children's social anxiety, cognitive overload, performance anxiety, and articulation challenges. We propose an alternative approach to obtaining language samples capitalizing on the widespread use of social media. Many children are freely creating language discourse through social media postings and chats. With proper consent, this discourse can be analyzed in lieu of language samples provided via direct elicitation. The described Analysis of Social Discourse Framework utilizes a popular, open source, natural language processing toolkit developed in Python to conduct language sample analysis on input language samples, such as social media text, in a manner that is more accurate, more comprehensive and easier to conduct than both the manual analysis and the commercial PC-based tool available in the market place. In addition to providing new metrics, the open source nature of ASDF means that future metrics can be added easily to the software as

researchers develop innovative methods to evaluate language samples. To validate the software tool, we used a variety of language samples from varied sources. Results show that the ASDF framework can conduct analysis of language samples providing a superset of the metrics currently in use by language therapists.

Looking forward we consider that at this time, the framework does not provide analytical abilities against historical data or against data sets from other sources. For example, the SLP cannot compare a child's performance against normalized performance of other children in the same age group having the same diagnosis. This is not something that can be done today either with existing manual processes, but if the ASDF gains wide adoption this will be a useful feature to augment current approaches. The collection of samples today requires that the therapist copies and pastes the text into a folder for processing. While copying and pasting text is a much simpler process than the current alternative approach of managing voice recorders, transcribers, and commercial PC-based software, it is still an extra step that we would like to eliminate. In the future, we would like to connect the ASDF to Facebook via the Facebook API to allow for fully automated analysis without the intermediate step of copying and pasting text. A gap remains in our framework in that it analyzes text-based language samples. While language sample analysis is primarily focused on language, the elicitation of speech samples does help the speech and language pathologists in identifying issues with their clients' speech, which cannot be done using the Analysis of Social Discourse Framework. However, our work on the LEXY framework opens another venue for analyzing spoken text via collecting samples from an interaction between a digital voice assistant, such as Amazon Alexa, or chatbots built on LEXY, and the children. Future research can thus study whether spoken language samples can be collected from

children interacting with voice assistants, and whether those samples can be automatically analyzed for speech problems.

Video Modeling Survey

Rapid advances in technology are improving many aspects of our lives but fall short when it comes to classrooms for students with special needs. An example of this is clear when it comes to video modeling interventions. Those interventions have been studied for decades in the scientific community. Their efficacy has been shown repeatedly. Yet, a simple review of published research on the mechanics of the process reveals the human factors limitations in attempting to apply those interventions in classrooms for students with special needs. While a time consuming, multi-step process may not hinder researchers from conducting case studies it does impose limits on the ability of already stretched-thin teachers to implement those processes in their real-life classrooms.

Schaeffer, et al. (2016) explained that the already stretched thin teachers are not implementing video self-modeling with efficacy and illustrated how this intervention can be applied with efficacy, providing practical examples. Their significant work covered methodology procedures, such as length of interventions, planning for interventions, interviewing parents, goal planning, etc. but in doing so further unmasked the human factors limitations involved in creating the video models, describing the need for multiple people, video editing software, tripods, tablets, transfer to DVD and other human factors requirements for the success of the process. In our view, those requirements are not practical for teachers in real life educational settings.

As our survey shows teachers of students with special needs do not shy away from using technology when it is easy-to-use and adds value to their classrooms. Thus, there is a need for developing easy-to-use applications that allow teachers to efficiently implement proven interventions in their classrooms. In addition to ease of use, time efficiency is important, especially considering the demands on the teachers' time. Time efficiency is not only a consideration when recording or playing videos but when analyzing data, interfacing with parents and applying interventions to multiple students.

Drawing on our experience, the results of our survey, and anecdotal evidence and interviews with teachers for students with special needs, we provide the following nine principles that can be followed when building an application for administering and tracking video modeling interventions in classrooms for students with special needs. We feel that applying those principles will lead to considerably wider awareness and adoption of those interventions by educators in educational settings.

1. Ease of use
2. Time efficient user interface
3. Ability to track multiple students and switch between students with ease
4. Ability to record models of target skills and behaviors directly within the app, both at school and outside of school settings
5. Ability to track behaviors, interventions, and responses to interventions with minimal keystrokes and clicks
6. Ability to play video models for children concurrent with the onset of interfering behaviors

7. Ability to track, analyze and correlate interventions with results
8. Ability to share results with parents
9. Availability of reports that can easily be included in Individual Education Plans

The AIX Framework

The AIX framework allows for the development of classroom applications for applying and tracking interventions and interfacing with parents in real-time. The major questions facing such applications are teachers' adoption, and how to handle privacy issues. A growing class of commercial applications, such as Class DoJo (<https://www.classdojo.com/>) and Brightwheel (<https://mybrightwheel.com>), as well as our own survey and pilot case study show that teachers are willing to use smartphone apps in their classrooms. Our framework uniquely adds the ability to administer and track interventions for students with special needs. Both the AIX framework and the commercial applications have tackled the privacy question by not requiring privately identifying information.

Our framework further introduces the novel concept of the parent and student owning their data, while allowing access to teachers and therapists. Earlier in the dissertation we have discussed the challenges with longitudinal tracking of the natural history of individuals with special needs and referenced how the CDC identifies this as one of the big challenges in offering long term services to individuals with special needs, especially as they age out of schools and into adulthood. Applications developed on top of the AIX framework allow parents and caregivers to characterize the natural history of children with special needs over the course of their school career.

The results of our case study validate that an easy-to-use mobile app will be used by teachers of students with special needs, and that it adds value, instead of adding overhead to their already busy schedules. Post study, several teachers, from multiple schools, have requested access to the application so that they can use it to track interventions in their own classrooms.

A secondary result of our case study is that the child reduced interfering behaviors as the study progressed and maintained that reduction once the interventions were withdrawn. We are careful not to generalize this result as it was applied to a single student, and the observations were recorded by the teacher and not an independent observer. Nonetheless, this result matches what Buggy (2005), and Bellini and Akullian (2007), found in their studies with children with autism, where video modeling interventions reduced interfering behaviors. Therefore, we conclude that an opportunity for future study exists whereby a larger study encompassing multiple children with Fragile X, planned according to single subject research methodology, can be conducted to further affirm whether visual model token-based response cost intervention can reduce interfering behaviors in children with Fragile X.

The LEXY Framework

The LEXY framework successfully modeled typical activities that are traditionally handled through paper based augmentative and alternative communication tools. Conversational interfaces are spreading rapidly and offer an opportunity for interfacing with children with cognitive and related disabilities. The LEXY framework uniquely allows parents to curate the model of the world, solving a major barrier to utilizing conversational interfaces in support of children with special needs. We successfully modeled First/Then activity boards, schedule boards, and coping boards using the LEXY framework. We successfully simulated interactions

between an actual chatbot built on top of the LEXY framework and simulated input from a parent and a child interacting with the chatbot. The results validate that the LEXY framework can successfully model existing paper based augmentative and alternative communication tools using a conversational, natural language processing interface.

Future areas of research include conducting case studies to validate that the chatbots will successfully work for children with special needs.

Tying It All Together

While the focus of this dissertation is children with intellectual disabilities it is important to note that other population groups that present with similar cognitive profiles could benefit from advances in the software tools presented in this work. Individuals with traumatic brain injuries, victims of strokes, seniors suffering from dementia and Alzheimer's disease, and some individuals dealing with post-traumatic stress disorder can all benefit from the software frameworks and tools developed in this dissertation, especially the LEXY framework. A very recent report released in February of 2018 argues for the case of using voice assistants for the aging population, as well as presents a real-life case of a senior citizen using the Amazon Echo to improve her quality of life post a stroke (Ageinplacetechnology.com, 2018).

The LEXY framework presents the biggest potential for developing a purpose-built conversational chatbot that can become an assistant, or a companion, to children with cognitive disabilities. In the future, we will extend the framework to support more storyboards and activities than currently supported and to add the concepts of skills and roles. More activities and storyboards would allow more scenarios for supporting the children, for example, adding a "communicating-feelings" activity would allow the child to trigger the chatbot to describe an

emotional state by simply stating a short phrase. A skill would allow future components to be developed for the chatbots. For example, a component to allow higher functioning, self-aware, children to record their anxiety level, including context, so that a caregiver or a therapist could work with the child at a later time on helping her/him cope with their anxiety.

Currently, the LEXY framework orchestrates logic based on the input utterances, but it does not enforce roles. For instance, when the caregiver informed the chatbot that “we are going home”, the chatbot processed the request, regardless of who actually uttered the phrase. In the future, LEXY can assign roles to its users, a parent role, a teacher role, a therapist role, and a sibling role, for example. The chatbot can then follow different rules per the user’s role.

Combining the AIX framework and the LEXY framework would allow us to develop conversational applications that can characterize the natural history of children with Fragile X by allowing them, and their caregivers, teachers and therapists, to track events, milestones and activities conversationally into a longitudinal database.

Our goal is to build on the technologies introduced in this dissertation to create a purpose-built conversational assistant that can aid children with intellectual disabilities achieve a higher quality of life.

An opportunity exists to improve support for children with special needs through incorporating technology into the design and development of human-centered solutions that empathize with those children and considers their point of view, and the point of view of parents, teachers and therapists, in the design of the solution. Work presented in this dissertation is a small, first step, in the effort to fulfil that opportunity.

APPENDIX A: APPROVAL OF HUMAN RESEARCH



University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901, 407-882-2012 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

NOT HUMAN RESEARCH DETERMINATION

From : **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To : **Ahmad Abualsamid**

Date : **October 04, 2016**

Dear Researcher:

On 10/04/2016 the IRB determined that the following proposed activity is not human research as defined by DHHS regulations at 45 CFR 46 or FDA regulations at 21 CFR 50/56:

Type of Review: Not Human Research Determination
Project Title: Tracking effects of Visual Models and Video Models on Behavior of Cognitively Impaired Children
Investigator: Ahmad Abualsamid
IRB ID: SBE-16-12522
Funding Agency:
Grant Title:
Research ID: N/A

University of Central Florida IRB review and approval is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are to be made and there are questions about whether these activities are research involving human subjects, please contact the IRB office to discuss the proposed changes.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

A handwritten signature in black ink, appearing to read "Patria Davis".

Signature applied by Patria Davis on 10/04/2016 11:33:03 AM EDT

IRB Coordinator

**APPENDIX B: FULL LANGUAGE SAMPLE ANALYSIS OF THINK
DIFFERENT POEM**

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('maybe', 'RB'),
('misfits', 'VBZ'),
('never', 'RB'),
('no', 'DT'),
('not', 'RB'),
('of', 'IN'),
('on', 'IN'),
('ones', 'NNS'),
('only', 'RB'),
('or', 'CC'),
('pegs', 'JJ'),
('people', 'NNS'),
('planet', 'VBP'),
('praise', 'NN'),
('push', 'NN'),

('quo', 'NN'),
 ('quote', 'NN'),
 ('race', 'NN'),
 ('re', 'NN'),
 ('rebels', 'NNS'),
 ('red', 'JJ'),
 ('respect', 'NN'),
 ('round', 'NN'),
 ('rules', 'NNS'),
 ('s', 'VBP'),
 ('see', 'VBP'),
 ('silence', 'NN'),
 ('sit', 'VB'),
 ('some', 'DT'),
 ('song', 'NN'),
 ('square', 'NN'),
 ('stare', 'NN'),
 ('status', 'NN'),
 ('t', 'NN'),
 ('that', 'IN'),
 ('the', 'DT'),
 ('them', 'PRP'),
 ('these', 'DT'),
 ('they', 'PRP'),
 ('thing', 'NN'),
 ('things', 'NNS'),
 ('think', 'VBP'),
 ('to', 'TO'),
 ('tools', 'VB'),
 ('troublemakers', 'NNS'),
 ('vilify', 'IN'),
 ('we', 'PRP'),
 ('wheels', 'NNS'),
 ('while', 'IN'),
 ('who', 'WP'),
 ('with', 'IN'),
 ('work', 'NN'),
 ('world', 'NN'),
 ('written', 'VBN'),
 ('you', 'PRP'),
 ('', 'VBP')],

'part_of_speech_tags_dict': {'IN': [('of', 3), ('in', 2), ('for', 2), ('because', 2), ('at', 2)],
 'NN': [('s', 1), ('round', 1), ('pegs', 1), ('square', 1), ('fond', 1)],
 'NNS': [('ones', 4), ('things', 2), ('people', 2), ('misfits', 1), ('rebels', 1)],
 'VB': [('see', 2), ('praise', 1), ('disagree', 1), ('quote', 1), ('disbelieve', 1)],
 'VBN': [('been', 1), ('written', 1)],

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'VBP': [('see', 3), ('have', 2), ('are', 2), ('', 1), ('change', 1),  
'VBZ': [('', 2), ('holes', 1), ('is', 1)]},  
'percent_of_content_words': 53.14009661835749,  
'words_per_vocab': 1.9714285714285715}  
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