

Chapman University

Chapman University Digital Commons

Computational and Data Sciences (PhD)
Dissertations

Dissertations and Theses

Summer 8-2020

Gaining Computational Insight into Psychological Data: Applications of Machine Learning with Eating Disorders and Autism Spectrum Disorder

Natalia Rosenfield

Chapman University, stewa165@mail.chapman.edu

Follow this and additional works at: https://digitalcommons.chapman.edu/cads_dissertations



Part of the [Data Science Commons](#), and the [Psychology Commons](#)

Recommended Citation

N.S. Rosenfield, "Gaining computational insight into psychological data: Applications of machine learning with eating disorders and autism spectrum disorder", Ph.D. dissertation, Chapman University, Orange, CA, 2020. <https://doi.org/10.36837/chapman.000182>

This Dissertation is brought to you for free and open access by the Dissertations and Theses at Chapman University Digital Commons. It has been accepted for inclusion in Computational and Data Sciences (PhD) Dissertations by an authorized administrator of Chapman University Digital Commons. For more information, please contact laughtin@chapman.edu.

Gaining Computational Insight into Psychological Data:
Applications of Machine Learning with Eating Disorders and
Autism Spectrum Disorder

A Dissertation by
Natalia Stewart Rosenfield

Chapman University
Orange, CA

Schmid College of Science and Technology

Submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in Computational and Data Sciences

August 2020

Committee in charge:

Erik Linstead, Ph.D., Chair

David Frederick, Ph.D.


Adrian Vajiac, Ph.D.




CHAPMAN UNIVERSITY
SCHMID COLLEGE OF SCIENCE AND TECHNOLOGY

Computational and Data Sciences

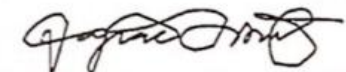
The dissertation of Natalia Stewart Rosenfield is approved.



Erik Linstead, Ph.D., Chair



David Frederick, Ph.D.



Adrian Vajiac, Ph.D.

July 2020

Gaining Computational Insight into Psychological Data: Applications of
Machine Learning with Eating Disorders and Autism Spectrum Disorder

Copyright © 2020

by Natalia Stewart Rosenfield

ACKNOWLEDGEMENTS

At the end of this wonderful journey, I would like to thank everyone who has supported me and helped me through this process. First, I would like to acknowledge and thank Dr. Erik Linstead for all the opportunities he has given me throughout my years at Chapman, including access to the MLAT Lab resources. I would not be where I am today without his guidance and support, both professionally and personally. I appreciated his honest feedback and commitment to see me succeed. He truly made my Chapman experience unforgettable.

I also want to thank my committee members, Dr. Dave Frederick and Dr. Adrian Vajiac, for their guidance and support during my time at Chapman. They gave me the foundational tools I needed to continue with my education and achieve this incredible goal. A special thanks to Dr. Frederick for giving me access to his body satisfaction dataset, the largest dataset on body satisfaction to date, and including me in the analysis.

There are not enough words to thank my husband, Steven, for his unwavering support through this long journey. He has been my biggest supporter and advocate, and I would not have been able to get through this program without his constant encouragement and unconditional love. Thank you for believing in me. I must also thank my dog, Petey, for being the cutest companion and attending classes with me.

Thank you to my parents for being my biggest cheerleaders through life. Thank you for telling me I could be anything when I grew up and never doubting my success. Thank you to my brothers for going to every orchestra performance, every recital, every softball game, and every

graduation. Your support will always mean the world to me. Thank you to my grandparents, for their unconditional love and for being the best role models.

I would also like to thank everyone -- professors, faculty and colleagues -- who I have met and worked with throughout my experience. You kept me going through some extremely difficult times and believed in me throughout the entire program. You have made my time at Chapman incredible and I will forever cherish this time in my life. Thank you!

LIST OF PUBLICATIONS

- Rosenfield, N.S., Eiroa, E., Linstead, E., & Frederick, D. (2020). Analyzing Body Satisfaction via Clusters. *In Preparation*.
- Rosenfield, N. S. & Linstead, E. (2020). A Cluster Analysis: Exploring the Eating Disorder Examination Questionnaire, Clinical Impairment Assessment and Autism Quotient to Identify Eating Disorder Vulnerability. *Machine Learning and Knowledge Extraction. Under Review*.
- Rosenfield, N. S., Lamkin, K., Re, J., Day, K., Boyd, L., & Linstead, E. (2019). A Virtual Reality System for Practicing Conversation Skills for Children with Autism. *Multimodal Technologies and Interaction*, 3(2), 28. doi:10.3390/mti3020028.
- Boyd, L. E., Day, K., Stewart, N., Abdo, K., Lamkin, K., & Linstead, E. (2018). Leveling the Playing Field: Supporting Neurodiversity Via Virtual Realities. *Technology & Innovation*, 20(1), 105-116. doi:10.21300/20.1-2.2018.105.

ABSTRACT

Gaining Computational Insight into Psychological Data: Applications of Machine Learning with Eating Disorders and Autism Spectrum Disorder

by Natalia Stewart Rosenfield

Over the past 100 years, assessment tools have been developed that allow us to explore mental and behavioral processes that could not be measured before. However, conventional statistical models used for psychological data are lacking in thoroughness and predictability. This provides a perfect opportunity to use machine learning to study the data in a novel way. In this paper, we present examples of using machine learning techniques with data in three areas: eating disorders, body satisfaction, and Autism Spectrum Disorder (ASD). We explore clustering algorithms as well as virtual reality (VR).

Our first study employs the k-means clustering algorithm to explore eating disorder behaviors. Our results show that the Eating Disorder Examination Questionnaire (EDE-Q) and Clinical Impairment Assessment (CIA) are good predictors of eating disorder behavior. Our second study uses a hierarchical clustering algorithm to find patterns in the dataset that were previously not considered. We found four clusters that may highlight the unique differences between participants who had positive body image versus participants who had negative body image. The final chapter presents a case study with a specific VR tool, Bob's Fish Shop, and users with ASD and Attention Deficit Hyperactivity Disorder (ADHD). We hypothesize that, through the

repetition and analysis of these virtual interactions, users can improve social and conversational understanding.

Through the implementation of various machine learning algorithms and programs, we can study the human experience in a way that has never been done. We can account for neurodiverse populations and assist them in ways that are not only helpful but also educational.

TABLE OF CONTENTS

	<u>Page</u>
ACKNOWLEDGEMENTS	IV
LIST OF PUBLICATIONS	VI
ABSTRACT.....	VII
LIST OF TABLES	XI
LIST OF FIGURES	XII
LIST OF ABBREVIATIONS	XIII
1 INTRODUCTION.....	1
1.1 Topics in Psychology	2
1.1.1 Eating Disorders.....	2
1.1.2 Body Satisfaction.....	3
1.1.3 ASD.....	3
1.2 Machine Learning	6
1.2.1 Hierarchical Clustering	7
1.2.2 Virtual Reality.....	8
1.3 Dissertation Organization	10
2 FIRST STUDY: EXPLORING THE EATING DISORDER EXAMINATION QUESTIONNAIRE, CLINICAL IMPAIRMENT ASSESSMENT AND AUTISM QUOTIENT TO IDENTIFY EATING DISORDER VULNERABILITY	12
2.1 Introduction.....	12
2.1.1 Factors in Manifestation	13
2.1.2 Previous Research.....	15
2.1.3 Current Assessment Tools	15
2.1.4 Treatment.....	18
2.1.5 Machine Learning	19
2.2 Method.....	20
2.2.1 Dataset.....	20
2.2.2 Survey Measures.....	21
2.2.3 Clustering Model	23
2.2.4 Validation Measures	24
2.3 Results.....	25
2.3.1 Clusters	25

2.3.2	Radar Plots	28
2.4	Discussion	30
2.5	Conclusion	32
3	SECOND STUDY: ANALYZING BODY SATISFACTION VIA CLUSTERS.	33
3.1	Introduction.....	33
3.2	Method.....	34
3.2.1	Unsupervised Learning	34
3.2.2	Hierarchical Clustering	35
3.2.3	Feature Selection.....	36
3.2.4	Radar Plots	39
3.3	Results.....	41
3.3.1	Clusters	42
3.4	Discussion	43
4	THIRD STUDY: A VIRTUAL REALITY SYSTEM FOR PRACTICING CONVERSATION SKILLS FOR CHILDREN WITH AUTISM	45
4.1	Introduction.....	45
4.2	Related Work	46
4.3	Theory to Practice	48
4.3.1	Bob’s Fish Shop.....	49
4.3.2	VirtualBlox	50
4.4	Technology: Bob’s Fish Shop System.....	52
4.5	System Development	54
4.5.1	Scenario.....	54
4.5.2	Implementation	55
4.6	Functionality	57
4.7	System Validation.....	59
4.7.1	Data Collection	60
4.7.2	Analysis.....	60
4.8	Results.....	60
4.8.1	Immersive	60
4.8.2	Malleable.....	61
4.8.3	Social Reciprocation	61
4.9	Implications for Future Practice.....	62
4.10	Conclusions.....	63
5	CONCLUSION	65
	REFERENCES.....	68

LIST OF TABLES

	<u>Page</u>
Table 3-1 This is a snapshot from the final output of our hierarchical clustering model algorithm. It is important to note that there are only four scores that remain in our output: Face Satisfaction, Overweight Preoccupation, BIQLI and Surveillance.	39
Table 3-2 This is a snapshot from the final dataset. We merged the sex column from the original data file so that we can separate the dataset into males and females.	40
Table 3-3 Table of scaled male average scores for each feature, used to produce the radar plot.	40
Table 3-4 Table of scaled female average scores for each feature, used to produce the radar plot.	40
Table 3-5 Table of summary statistics for BMI and Age of male participants.....	41
Table 3-6 Table of summary statistics for BMI and Age of female participants.	42

LIST OF FIGURES

	<u>Page</u>
Figure 2-1 Demographic data of participants. Numbers reflect 24 members in the control group (HC) and 20 members in the clinical group (AN-WR).....	21
Figure 2-2 K-means clustering model results for $k=2$	26
Figure 2-3 The final output of our analysis. Table displays participant number, group assignment, cluster assignment, and CIA, AQ and EDE-Q scores.....	27
Figure 2-4 Confusion matrix for the k-means clustering model.....	27
Figure 2-5 Plot of Silhouette Method showing the optimal number of clusters is 2.	28
Figure 2-6 Radar plot of results when the data is scaled from 0 to 1.	29
Figure 2-7 Radar plot of results when using z-score to scale the data.....	29
Figure 3-1 Dendrogram produced by our hierarchical clustering algorithm. The dotted line indicates the final four clusters.	36
Figure 3-2 Radar plot for males with four final clusters.....	38
Figure 3-3 Radar plot for females with four final clusters.....	38
Figure 4-1 Bob’s Fish Shop: Screenshot of shop owner greeting the VR user.	50
Figure 4-2 Screenshot of VirtualBlox block sorting game.	52
Figure 4-3 The Oculus Rift headset and microphone used for voice input.	53
Figure 4-4 Image of Bob making eye contact with user.....	53
Figure 4-5 Diagram of the software components for Bob’s Fish Shop.	55
Figure 4-6 Sample of system output.	57

LIST OF ABBREVIATIONS

<u>Abbreviation</u>	<u>Meaning</u>
ADHD	Attention Deficit Hyperactivity Disorder
AN	Anorexia Nervosa
AQ	Autism Quotient
ASD	Autism Spectrum Disorder
BCBA	Board Certified Behavior Analyst
BIQLI	Body Image Quality of Life Inventory
BMI	Body Mass Index
CIA	Clinical Impairment Assessment
CNN	Convolutional Neural Network
DSM	Diagnostic and Statistical Manual of Mental Disorders
MACH	My Automated Conversation coach
VR	Virtual Reality
VRE	Virtual Reality Environment

1 Introduction

The field of psychology is a relatively new science, officially recognized as its own discipline in 1879 [1]. Before the science was developed, people were still interested in the topics that psychologists study today. Philosophers have been studying the human experience since as early as 400 B.C., both physically and mentally [1]. However, at that time there was no way to measure the mental faculties in any reliable way; rather, it was all speculation and introspection.

Over the past 100 years, assessment tools have been developed that allow us to explore mental and behavioral processes that could not be measured before. Psychologists now use objective measures and the scientific method to create experiments that are valid and reproducible. More recently, with the invention of computers, we can access, produce, and reproduce research quicker than ever. Conventional statistical models used for psychological data are lacking in their thoroughness and predictability. Machine learning algorithms allow us to understand and interpret the data in a way that is unique.

In recent years there has been an increased interest in applying machine learning to psychological data, particularly in the field of Autism Spectrum Disorder (ASD) [2] [3] [4] [5] [6] [7] [8] [9] [10] [11] [12] [13].

Because machine learning in this discipline is so new, there are endless opportunities for research. This dissertation presents examples of using machine learning techniques with data in three areas: eating disorders, body satisfaction, and ASD [14] [15] [16] [17].

1.1 Topics in Psychology

1.1.1 Eating Disorders

Eating disorders, particularly anorexia nervosa (AN), has the highest mortality rate when compared to all other mental disorders [18] [19]. Considering there are over 150 clinically diagnosable mental disorders in the Diagnostic and Statistical Manual 5th Edition (DSM-V), special attention must be given to understanding and treating this disorder. However, this proves to be a challenging subject because much is still unclear as to how one develops this disorder; as some researchers note, there is very little exploration on this topic [20].

There are many factors that can influence someone to develop an eating disorder, and it is often a combination of biological, social, cultural, and psychological factors that develop into a disorder. According to the DSM-V, eating disorders can be categorized into six subtypes: pica, rumination disorder, avoidant/restrictive food intake disorder, AN, bulimia nervosa, and binge-eating disorder [21].

Interestingly, symptoms can fluctuate and evolve throughout the span of the disorder. The same factors can manifest as different subtypes for different people, or they can manifest as different subtypes in any one person over the course of a lifetime. As a result, the diagnosis and treatment of eating disorders are extremely involved and complicated. Additionally, of the studies showing favor towards one form of treatment, replication studies have not been successful [20]. This provides a perfect opportunity to use machine learning to study the data in a novel way.

1.1.2 Body Satisfaction

One factor that has been consistently linked to eating disorders is body satisfaction. In fact, there is an entire subgroup of assessment tools for eating disorders that focuses on body image and body satisfaction. Attractiveness has always been, and will probably always will be, part of our lives and of our society. Today is no different; we are influenced, now more than ever, by the media. News channels, social media platforms, video chats, streaming and live recordings are instantly accessible to everyone with a device.

Scientific research of any kind on the connections between body image and life satisfaction was not considered until the mid-1900s, less than 100 years ago. It wasn't until the 1950s that any sort of experiment was conducted to explore the relationship between body image and life satisfaction [22], and most of the research did not begin until the 1970s [23]. Even now, there is remarkably little research on body image and body satisfaction, despite its prevalence in our culture and society. Of the research available, simple statistical models were used to analyze the data [22] [23] [24].

1.1.3 ASD

ASD is one area of psychology that has quite a bit of research. The definition of ASD has changed over the years; the DSM-IV defined autism as an umbrella term that encapsulated different subtypes of autism, ranging from low functioning to high functioning. The DSM-V does not have any subtypes, but rather combines all subtypes under ASD. Practitioners still take note of the severity of symptoms. Though there are some implications that arise due to the changing of terms and definitions, they do not apply to the research presented in this paper.

ASD is defined in the DSM-V as “persistent deficits in social communication and social interaction across multiple contexts.” [25] ASD is often accompanied by restrictive, repetitive behaviors and may also include intellectual or language impairment. While the mortality rate is low, its prevalence rate is extremely high; research now estimates that one in 54 children are diagnosed with ASD [26]. Because of the pervasiveness of the disorder, careful consideration must be made regarding the diagnosis and treatment.

However, not all view ASD as a disorder. Neurodiversity is a term that encapsulates the diverse expression of human neurological development, resulting in a wide variety of sensory perceptual abilities. Many of these unique sensory traits are clustered by diagnostic labels, such as Autism Spectrum Disorder (ASD), Sensory Processing Disorder, Attention-Deficit/Hyperactivity Disorder (ADHD), Rett syndrome, dyslexia, and so on.

The Neurodiversity Movement formed specifically to reshape how ASD is perceived [27] over the last 30 years because many support Sinclair’s belief that ASD is just another part of the human experience, a variation of brain functioning [28] [29]. Disorders are typically associated with deficits or abnormalities, but Sinclair and other advocates of the Neurodiversity Movement argue that ASD brings about differences rather than deficiencies [30]. As Sinclair [29] states, “Autism is a way of being. It is not possible to separate the autism from the person.” This leads to another level of difficulty when diagnosing and treating ASD because some do not see it as a problem that needs to be fixed [30].

This has important implications, not only for those living with ASD but for people with other neuro-divergent conditions that would benefit from technologists expanding the ways that information is transmitted through technology. In fact, many people in our society could benefit

from the translational work of applying what is known about the strengths and weaknesses of neuro-diverse populations to the design of assistive technologies. ASD is often accompanied by sensory sensitivities, and 1 in 20 children have been found to have a sensory processing disorder [31]. It is imperative, then, that we focus on making technologies and life experiences more accessible to people with sensory differences.

Certain difficulties can arise with ASD and there are many avenues for help in the detection and management of such difficulties. Professionals use diagnostic in-person interviews to confirm that the individual meets the criteria as defined in the most current version of the DSM.

However, since ASD can be detected as early as age two, diagnostic interviews and written tests are not always appropriate measures. Instead, practitioners can use observational studies to determine if the individual meets four criteria, as explained in the DSM-V: Deficits in verbal and nonverbal communication; repetitive and inflexible behaviors; symptoms present themselves during early development; symptoms cause significant impairment [25].

It may be no surprise that the treatment of ASD is also complicated and multi-faceted. There is no cure for ASD; researchers and practitioners concentrate more on the management and understanding of ASD with therapeutic tools, though medication is also widely used, and may be required in extreme cases, to subdue some of the symptoms. ASD effects all areas of a person's life and is often comorbid with other disorders and challenges. As a result, the therapy used is unique to the individual and must be flexible with time. The most widely used therapies include Cognitive Behavior Therapy, Applied Behavior Analysis Therapy, and more recently virtual reality (VR). ASD therapy that works with one individual may not work with another, which provides another layer of complexity when creating a management plan. It would be extremely

beneficial to researchers and practitioners if there was data on the accuracy and predictability of these measures.

1.2 Machine Learning

Machine learning algorithms can be classified as either supervised or unsupervised learning. We used a semi-supervised machine learning algorithm in the first study of this dissertation and an unsupervised algorithm in the second study.

Supervised learning occurs when the researchers have access to the truth data. The algorithm takes an input, classifies it, and is then provided with corrective feedback [32]. This immediate feedback contributes to improved learning and accuracy of the model over time. Supervised learning is especially useful in the prediction of future inputs [33]. Unsupervised learning is just the opposite; the data is unlabeled and the patterns are found heuristically [34]. It is very common with real-world data to not have access to the truth data, either because that data is unavailable or was never collected, and thus unsupervised models are more applicable. It is also possible to combine the two models in a semi-supervised technique, where the researcher allows the algorithm to find the patterns heuristically and then uses truth values to guide the model to better predictions.

Regardless of if we are studying eating disorders, body satisfaction, or ASD, there are a multitude of different diagnostic tools, treatments, and therapies available today, and which tools are utilized is at the discretion of the professional. Machine learning can help us differentiate the tools that perform better. In this dissertation we employed hierarchical clustering models for the first two studies to examine the value of certain diagnostic tools, and in the last study we present and discuss VR as a therapeutic tool for those diagnosed with ASD.

1.2.1 Hierarchical Clustering

The aim of hierarchical clustering is to determine if there is any natural structure or arrangement to the data [35]. Often, knowing the similarity (or dissimilarity) of objects assists researchers in making significant conclusions. However, the underlying structure may not be evident just by looking at the dataset [35]. Hierarchical clustering models give researchers the insight needed to see any relationships in the data that were not previously considered. Another key benefit to hierarchical clustering models is that little knowledge is needed by the researcher prior to running the analysis [36].

Clustering models are flexible and improve in accuracy and predictability over time. The goal is to separate the dataset into clusters, where the points within the clusters are more similar than the points between clusters [37]. The algorithm assigns each data point to the most appropriate cluster using an iterative process, and re-evaluates the assignments until an optimal number of clusters is reached [36]. There are two approaches, depending on what algorithm is used. They are known as top-down processing, where all points begin as one cluster and more dissimilar points are separated into their own clusters, or bottom-up processing, where each point begins as its own cluster and more similar clusters are merged. In chapter 3 we discuss a hierarchical clustering algorithm that uses bottom-up processing.

One model that uses top-down processing is the k-means clustering algorithm, which we present in chapter 2. The algorithm divides the data into k clusters, where k is a value that is determined prior to analysis. The cluster is represented by its mean value, the centroid [38]. The main goal of the k-means clustering algorithm is to minimize intra-cluster variation, meaning that the datapoints within each cluster are similar [38]. There are several ways to calculate the distances

between points and the researcher may choose which approach is the most appropriate. The most common, and what was used by MacQueen in his original paper, is the Euclidean distance [39].

1.2.2 Virtual Reality

While VR is not a new concept, beginning as a theory found in science fiction books and movies, its prevalence in our day-to-day life has increased exponentially in the last 10 years. The cost for a VR device has become so inexpensive that anyone can purchase one for personal use.

Furthermore, its adaptability to many domains has led researchers and professionals to consider VR as a potential therapeutic and educational tool for children and adults alike. VR can be fully immersive, augmented, 2D or 3D; regardless of the specifics of each system, researchers agree that VR must include hardware, such as computers, head-mounted displays, or gloves [40] [41].

Research shows that better treatment leads to better outcomes [42]. Studies also indicate that VR-based treatments produce positive results for various mental health conditions [43].

Unfortunately, quality treatment is not always accessible, especially for those with lower socioeconomic status. VR allows effective treatment to reach anyone, regardless of income or living situation; it will directly impact the inconsistency of treatment often found across time [44]. VR also provides opportunities to engage with others, even when not physically together, and creates a safe environment for therapist-client interactions [45]. This offers many potential avenues for VR to be utilized, specifically when treating and managing psychiatric disorders [43].

Virtual reality (VR) has stepped to the forefront as a possible means of assistive therapy and accessibility. Since VR has become more affordable in the recent years, its use is now popular both in private industry and for entertainment purposes. What is even more appealing about VR

in regard to therapy is that the experience is dynamic, individualized, and personalized for the user's preferences. Due to the sensory processing differences in ASD, VR provides new opportunities mediated by technology to explore the world.

The possibility for VR technology to assist students with special needs is moving to the forefront of educational conversations as well. These VR spaces prove to be very useful to the user because there are no real-world risks, yet they are still able to navigate through the experience or lesson. For example, users can interact with avatars in a social situation without the pressure of making a mistake. One of the primary benefits of integrating VR technology into special education learning environments is that it provides interactive learning, enabling the learner to have control of his or her learning process [46] [47]. VR applications may allow students with ASD to participate more fully in general education classrooms and more so in society.

The goal of VR interventions for neurologically diverse individuals is to promote an alternative way of learning that provides a sense of belonging from the perspective of someone with ASD in all settings; the aim of technology need not be focused on impairment but rather on building self-esteem and supporting creativity [48]. Using technology allows the user to insert oneself into various situations, no matter where the user is physically. Additionally, technologies that support nonverbal skills can build a bridge between the normative and neuro-diverse experiences, what some researchers refer to as “neuro-shared spaces” [49].

Research states that users of this interactive therapy can experience “reduced stress from the lack of nonverbal signals, the ability to find people with similar interests, and pre-defined interaction mechanisms, like birthday greetings” [50]. In the current work, we describe two sensory-friendly

environments, Bob’s Fish Shop and VirtualBlox. Though we focus on ASD, these techniques provide an opportunity for generalization.

Researchers of assistive technology are calling for more customization and systems capable of adapting to multiple use cases; achieving this requires multiple iterations with special attention to interface design [51]. Adoption may be improved by including users with neurodiversity, such as ASD, across all the stages of development in addition to their caregiver networks. Many researchers have found their technologies have limitations and suggest that iterating with users would be a step toward solutions—whether this iteration occurs at the beginning of the lifecycle, or during or after development [51]. The common themes across these works are usability, acceptance, and adoption. VR is now a commercial commodity that leverages infrastructure (e.g., the web) and provides a unique pathway to supporting neurodiversity.

1.3 Dissertation Organization

This dissertation presents four different studies and the structure is as follows. The first study is presented in chapter 2 and is an example of how machine learning can be helpful in the field of psychology. We use a k-means machine learning algorithm to explore eating disorder behaviors. The dataset is from the Department of Psychiatry and Behavioral Sciences at Duke University School of Medicine. We specifically looked at three variables in the dataset to build a clustering model that accurately assigns an individual to the appropriate group.

Chapter 3 is a preliminary analysis on a dataset that was created by Dr. Dave Frederick, from Chapman’s Crean College, along with his colleagues. It is the largest dataset on body image and body satisfaction to date. This is another instance where traditional statistical methods were

restrictive and one-dimensional in their results, so we used a hierarchical clustering model to determine the hidden patterns. Our results found four distinctive clusters in this dataset.

We switch subjects in chapter 4, focusing on using VR in educational settings. We particularly concentrate on children with ASD and how VR can enhance their learning experiences. In this chapter we introduce Bob's Fish Shop, a virtual reality tool that was developed in the MLAT Lab. We also present a case study, which tested the program's feasibility for children diagnosed with ASD and ADHD. We predict that this tool can be used to improve social interactions in educational as well as personal settings.

Studying these topics through the lens of machine learning offers us a new perspective. Instead of using basic statistical models to explain the data, we utilize machine learning to dive deeper into the underlying patterns and relationships. In addition, machine learning algorithms allow us to predict future behavior and the models become more accurate over time. The results in this dissertation support the hypothesis that machine learning algorithms find hidden patterns in the data that traditional statistics cannot detect. Additionally, we see that VR environments facilitate a safe and controlled setting for social interactions, both casual and professional.

2 First Study: Exploring the Eating Disorder Examination Questionnaire, Clinical Impairment Assessment and Autism Quotient to Identify Eating Disorder Vulnerability

2.1 Introduction

According to the Diagnostic and Statistical Manual of Mental Disorders 5th Edition (DSM-V), an eating disorder is defined by a “persistent disturbance of eating or eating-related behavior that results in the altered consumption or absorption of food” [21]. Currently, an eating disorder can be categorized into one of six subtypes: pica, rumination disorder, avoidant/restrictive food intake disorder, anorexia nervosa (AN), bulimia nervosa, and binge-eating disorder [21]. The data used in this analysis specifically focused on individuals with a previous diagnosis of AN [52].

A study conducted in 2010 found that 2.7% of US adolescents aged 13-18 experience a lifetime prevalence of eating disorders [53]. Some researchers report that 1 to 2% of individuals will develop an eating disorder, specifically AN, at some point; among adults, 0.6% experience a lifetime prevalence of AN [54]. Furthermore, Hudson and colleagues observed that 56.2% of adult participants who were diagnosed with AN also met the criteria for at least one other disorder. These disorders include anxiety disorders, mood disorders, impulse control disorders, and substance disorders [54].

Mortality rates have been reported at 5 to 8% [55]. There are also many other serious lifetime problems associated with eating disorders: heart failure, kidney damage, a compromised immune system, and other serious medical complications [56] [57]. Unfortunately, the rate of eating disorders has not decreased in recent years, even though effective treatments have become more available [58] [59].

2.1.1 Factors in Manifestation

Eating disorders are very complicated and many factors play a role in their manifestation. There are biological, sociocultural, and psychological components that effect each person differently, and what may manifest as an eating disorder in one person may not manifest itself in another [21] [57].

2.1.1.1 Biological

Certain biological traits are known to be associated with eating disorders. In fact, previous research has shown that as much as 84% could be due to genetic factors [60]. First-degree biological relatives of those diagnosed with an eating disorder are at an increased risk [21]. Historical research shows that females, Caucasian females in particular, are at a much greater risk for developing an eating disorder than any other group [54] [55] [57] [60]. Researchers have also been able to identify brain abnormalities in those diagnosed with AN using functional magnetic resonance imaging (fMRI) and other technologies [21] [52]. It has been concluded using fMRI scans that participants with a previous eating disorder diagnosis had reduced activation in the part of the brain responsible for social reward processing [52] [61]. Additionally, Sweitzer and colleagues [52] found that the longer the person had an eating disorder, the greater decrease in brain activation. Other researchers hypothesize that eating

disorders may be caused by neurochemical and hormonal imbalances, specifically in serotonin and dopamine levels, due to their relationship with reward experience [57] [62] [63] [64] [65] [66].

2.1.1.2 Sociocultural

It is no surprise that cultural influences must be considered when examining eating disorders. Post-industrialized, high-income cultures see the highest rates, where there are more intense fears of gaining weight [21]. Researchers have been able to connect eating disorders with the changing standards of beauty over time, with icons for women getting thinner and thinner [57] [67] [68] [69] [70]. Occupations that value thinness, such as models and athletes, are also known to be at greater risk of developing an eating disorder [21] [57]. Sundgot-Borgen [71] concluded that eating disorder behavior varied depending on what type of sport was played. Athletes in aesthetic sports or weight-dependent sports, such as gymnastics, figure skating and wrestling, were more likely to have an eating disorder than athletes in endurance, technical, or ball game sports [71].

2.1.1.3 Psychological

There are also psychological factors that influence an individual's eating behavior. Some researchers hypothesize that eating disorders may serve as a way to deal with painful emotions; studies show that those who engaged in emotional eating were at a much greater risk for developing an eating disorder [57] [56] [68] [72] [73]. Furthermore, individuals who have anxiety disorders are also at greater risk [21]. Other researchers have suggested that an obsession on appearance is directly related to eating disorder behavior [73] [74]. It has been determined over time that those at greater risk for an eating disorder exhibit more perfectionist and rigid

thinking patterns [55] [57] [75] [76]. Moreover, children who exhibit obsessional behaviors are more at risk for developing an eating disorder, particularly AN [21].

2.1.2 Previous Research

There have been many studies conducted in order to determine the effects of cultural and psychological influences on eating disorder behavior. For example, Stice and Shaw [77] concluded that young women who were exposed to images of fashion models reported more depression, insecurity, stress and body dissatisfaction than those who were not exposed to the images. Another group of researchers found that college-age women who were exposed to a cosmetic surgery makeover show were more likely to feel pressure to be thin than women who were exposed to a home improvement show [78]. Stice, Maxfield and Wells [79] demonstrated how social pressure can also influence behavior when exposed to others who are dissatisfied about their bodies. College women were more likely to feel dissatisfied with their bodies after they were exposed to someone complaining about weight, discussing extreme exercise routines and restrictive diet behavior [79].

2.1.3 Current Assessment Tools

In order to assess an individual for an eating disorder, he or she first needs a medical examination [80]. After the initial examination, there are many ways of assessing the magnitude of the eating disorder. As a result, it is up to the professional to decide which tools to use. The most accurate and popular form of assessment for eating disorders is a structured interview with a professional, using the most current edition of the DSM [80] [81] [82]. However, interviews are costly and time-consuming [82]. There are also many other problems that may arise when

diagnosing an eating disorder, including manipulative behavior, the reluctance to cooperate, and even denial of the disorder altogether [82] [83].

Eating disorders effect all areas of a person's life; some diagnostic tools focus on one specific facet of life, while other tools focus on a range of dimensions [82]. The assessment tools that are currently available can be categorized into five main groups: General measures, DSM questionnaires, screening questionnaires, body image assessments, and quality of life measures [82].

2.1.3.1 General Measures

General measures, including the Eating Disorders Inventory and the Eating Disorder Examination Questionnaire (EDE-Q), are used as early diagnostic tools and assess the core pathology symptoms related to the disorder, such as interpersonal insecurity, emotional dysregulation, low self-esteem and perfectionism [82]. These measures may also be used as a predictive tool, as they have been shown to perform well in clinical studies [82] [84] [85].

2.1.3.2 DSM Questionnaires

There are also diagnostic tools that are based on the current DSM criteria. These self-report questionnaires produce categorical results that are parallel to those in the DSM. In the Questionnaire for Eating Disorder Diagnoses, for example, it determines whether the participant has disordered eating patterns consistent with the DSM criteria or not; non-disordered eating individuals can then be labeled as asymptomatic, no symptoms, or symptomatic, showing symptoms but not enough to be diagnosed [82] [86]. Those who are in the disordered eating

category are then labeled based on the DSM criteria. These measures perform well, particularly when differentiating between symptomatic and asymptomatic diagnoses [82].

2.1.3.3 Screening Questionnaires

Screening questionnaires are much shorter than other self-report measures, sometimes including as little as five questions. The aim of these tests is to determine if an eating disorder is likely to exist [82]. Though these measures are short, studies have shown that they perform well with high validity [82] [87] [88] [89]. These questionnaires tend to focus on broad symptoms, such as fear of gaining weight and body perception; they are not intended to diagnose, but rather to raise awareness of a potential issue [82] [90]. Assessments include the Eating Attitudes Test [91], Bulimia Test [87] and the Clinical Impairment Assessment (CIA) [92].

2.1.3.4 Body Image Assessments

Body image has become increasingly important in the understanding of eating disorders, particularly because body image disorder is often seen occurring with AN [82]. Measures have been developed to evaluate concerns with body shape and size, such as the Body Shape Questionnaire [93] and Body Attitude Test [94]. These tools commonly focus on an individual's self-evaluation of body size and attitudes about gaining weight [95]. They may also include questions regarding social influences [96]. Body image assessments can be used as a preventative and predictive tool to indicate basic risk factors of eating disorders [82] [96].

2.1.3.5 Quality of Life Measures

Other measures have been developed to determine the impact of an eating disorder on a person's overall quality of life. These tools aim to assess specific domains of daily life: Cognitive functioning, family and personal relationships, psychological and emotional health, physical health, and work or school life [82] [97] [98]. The Eating Disorders Quality of Life Instrument [97] and the Eating Disorders Quality of Life Scale [98] are the main tools used by professionals [82].

2.1.4 Treatment

Due to the variability in diagnosis and symptoms, treatment for an eating disorder is unique to the individual. This makes it difficult for professionals because there is no standard treatment plan. Some individuals recover after one episode, some experience fluctuating weight patterns and relapses over many years, while others may need hospitalization to fully recover [21].

Furthermore, studies show that about one third of patients with an eating disorder “continue to meet diagnostic criteria five years and longer after initial treatment” [99] [100], and as many as 40% of those diagnosed with an eating disorder will experience crossover between the various subtypes [21] [101]. This presents another difficulty when treating and diagnosing eating disorders because professionals can only diagnose current symptoms with the DSM [21].

It is still unclear if the abnormalities seen in those diagnosed with an eating disorder are the consequences or the causes of eating disorders [57]. In addition, most of us experience the same cultural pressures of being thin, though many individuals never struggle with an eating disorder [57]. Some researchers have concluded that those who internalize the thin ideal presented in our

culture are more likely to develop eating disorder behavior [79], though there is still much we do not comprehend about why someone does or does not internalize this cultural stigma.

2.1.5 Machine Learning

2.1.5.1 Clustering

Clustering is a technique used to find hidden patterns in data [102] [103]. These models allow us to visualize multi-dimensional data by organizing and grouping observations, where the groupings make some natural sense [103]. Clustering models most often use bottom-up processing, where each observation starts as its own group and they are iteratively grouped together until an optimal and natural number of clusters has been reached. Clustering has been known to improve performance in many applications [103] [104]. There are three main types of clustering techniques: hierarchical clustering, Bayesian clustering, and partitional clustering [103] [105]. The results in this paper are a result of using a hierarchical clustering model.

2.1.5.2 Semi-Supervised Learning

One of the many benefits to using machine learning is that it offers new insight into datasets that researchers may not previously have. Oftentimes, some knowledge is known or available to the researchers prior to analysis and may be used to guide the model [102]. Semi-supervised machine learning is beneficial because of its unique ability to use labeled and unlabeled data, which improves the model's ability to predict on future unlabeled data [103] [106].

2.2 Method

2.2.1 Dataset

The dataset used in this analysis was originally produced in 2018 by Dr. Maggie Sweitzer, Dr. Nancy Zucker, and Savannah Erwin from the Department of Psychiatry and Behavioral Sciences at Duke University School of Medicine. They used a Qualtrics survey to collect the data, Excel to clean the data, and SPSS for their analysis [52]. Researchers also calculated the total scores and subscale scores for the following, which will be discussed later in more depth: EDE-Q global score, CIA global score, and AQ total score.

The dataset originally included 54 participants, ages 19-32. Participants were split into two groups, clinical and control, and were matched on age, race, education, and medication status [52]. See Figure 2-1 for the summary statistic. Some observations were removed due to missing data, errors and other issues [52]. The final dataset used in the analysis included a total of 44 participants, 20 participants in the clinical group and 24 participants in the control group.

	HC	AN-WR
Demographics	n (%)	
<u>Race</u>		
Caucasian	18 (75.0%)	15 (75.0%)
African American	2 (8.3%)	1 (5.0%)
Asian	3 (12.5%)	2 (10.0%)
Indian	0 (0%)	1 (5.0%)
Native American	1 (4.2%)	0 (0.0%)
Not Reported	0 (0%)	1 (5.0%)
	Mean (SD)	
Age (years)	24.50 (3.65)	22.50 (3.65)
Education (years)	15.54 (1.61)	15.37 (2.50)
Comorbidity and Psychotropic Medication	n (%)	
Non-eating disorder Mental Illness Diagnosis	2 (8.3%)	6 (30.0%)
Current Psychoactive Medication Use	0 (0.0%)	3 (15.0%)

Figure 2-1 Demographic data of participants. Numbers reflect 24 members in the control group (HC) and 20 members in the clinical group (AN-WR).

Participants in the clinical group were required to have a previous diagnosis of AN as defined by the DSM-V, while also having maintained a healthy weight for at least six months [52].

Researchers used portions of the Structured Interview for Anorexia and Bulimia [107] as well as the EDE-Q [108] in order to measure onset, course and duration [52]. The control group participants were required to have no previous history with any form of eating disorder. They were also required to be free of psychiatric disorders, psychosis, substance use, and neurological disorders [52].

2.2.2 Survey Measures

Much of the dataset consists of personal information, such as race, age, years of education, height, and BMI. Additionally, the researchers asked the clinical group about details regarding their eating disorders, including age of onset, lowest weight, duration, and recovery time. They focused on these attributes, as well as fMRI scans, to explore social reward processing [52]. We chose to focus on the EDE-Q, CIA, and AQ scores so that our analysis offered novel results.

2.2.2.1 EDE-Q

The EDE-Q was developed in 1994 by Fairburn and Beglin and is based on the Eating Disorder Examination (EDE) that was previously created by Fairburn and Cooper in 1993. The EDE is a structured clinical interview, known for its excellent ability to assess eating disorders [80] [81]. However, the EDE is very time consuming, costly, and requires a trained professional to administer since it is an interview [109] [110]. Therefore, the EDE-Q was developed in order to allow individuals to self-report on their eating disorder [111]. The original version had 36 items, though newer versions have been developed with 28 items [108]. The EDE-Q includes a global score as well as scores for four subscales: restraint, shape concern, weight concern, and eating concern. It is scored using a 7-point Likert scale; each subscale item is converted to a number and then added and averaged to create one score per subscale [110] [111]. Higher scores indicate greater eating disorder expression. Researchers have determined that the EDE-Q is a reliable and accurate self-report measure, specifically on these four subscales [81] [112].

2.2.2.2 CIA

The CIA is a supplemental questionnaire, created by researchers Kristin Bohn and Christopher Fairburn in 2008. This measure was to be used alongside the EDE-Q to determine the overall severity of psychosocial impairment in areas that are typically affected by an eating disorder, including mood, self-perception, and work performance [109] [113]. The questionnaire is comprised of 16 items and scored with a 4-point Likert scale: “Not at all”; “A little”; “Quite a bit”; and “A lot”. These answers were scored as 0,1,2, or 3, respectively. Each participant’s answer was added together to produce the global CIA score as well as three subscale impairment

scores: personal, social and cognitive [109] [110] [113]. A higher score indicates more psychosocial impairment. Researchers have determined the CIA to be valid [113].

2.2.2.3 AQ

The AQ, developed by Simon Baron-Cohen and his fellow researchers in 2001, is a self-reported questionnaire designed to characterize participants who may have ASD. The questionnaire consists of 50 questions which assess five different areas: social skill, attention switching, attention to detail, communication, and imagination [114]. The possible responses are: “Definitely agree”; “Slightly agree”; “Slightly disagree”; “Definitely disagree”. There is a rubric to follow for scoring; each item can receive up to one point and the total number of points is the total AQ score [114]. Researchers determined that a score of 32 and above qualifies an individual as having “clinically significant levels of autistic traits” [114] [115]. Based on the results of Baron-Cohen’s research, the AQ is a valid assessment tool, both for adolescents as well as adults. Though the AQ is not directly related to eating disorder behavior, the original researchers included this score [52] and therefore we also included it in our analysis.

2.2.3 Clustering Model

Each participant was labeled in a Group column with *clinical* or *control*, however this column was removed prior to analysis so that our results were not influenced by this attribute. All data pre-processing steps, as well as the final analysis, were conducted using the R statistical computing software RStudio. Once the data was cleaned, scaled and ready to be analyzed, there were 32 remaining observations that were run through a k-means clustering model.

K-means uses an algorithm that aims to partition the data into k sets or groups [39]. It uses an iterative technique with two essential steps: Assignment and Recalculation. Consider a multidimensional data matrix E . Each data point can be thought of as a vector, x_i where $i = 1, 2, \dots, k$, that contains multiple attributes per observation.

The number of clusters must be chosen prior to analysis for k-means, so we chose to run the model for $k=2-5$. To begin, E is split into k groups. The mean value is calculated for each group and this value becomes the centroid.

1. Assignment

- a. For each new point $m \in E$, determine the closest centroid and assign m to this group. The distance is calculated using some distance measure. In this paper, we emulated MacQueen's original application of this algorithm [39] and used Euclidean distance:

$$T_i(x) = \{m: m \in E, |m - x_i| \leq |m - x_j|, j = 1, 2, \dots, k\}$$

2. Recalculation

- a. Recalculate the centroid value.

These two steps are repeated until the centroids no longer change.

2.2.4 Validation Measures

In this particular situation we had access to the truth data, so we know which participants were in the control and clinical groups. We used this information to validate our model by comparing the cluster results with the pre-labeled groups. We formed a confusion matrix and calculated our model's accuracy by adding the correctly labeled data points for each group and dividing by the total number of participants.

We also used an internal validation measure, the Silhouette Method, to further confirm that our results were accurate. The Silhouette Method was developed to validate partitioning techniques [116], using proximities between datapoints to create an easy-to-interpret graphical representation of the data. It utilizes a simple equation to determine a value between -1 and 1, which measures how well each datapoint has been classified [116]. However, unlike other validation measures, the Silhouette Method uses mean score and subtraction to relate compactness and separation, rather than division [117]. The final output is a plot of these values. To determine the optimal number of clusters, one simply looks for the value that corresponds to the highest peak in the graph. Roousseeuw [116] believed that the true benefit of this method was its interpretability and validity, specifically with clustering results. Research has shown that the Silhouette Method performs well compared to other validation measures [117].

2.3 Results

2.3.1 Clusters

See Figure 2-2 for the results from our k-means clustering model for our first model $k=2$. This model clustered the data as follows:

- Cluster 1: 13 participants
- Cluster 2: 19 participants

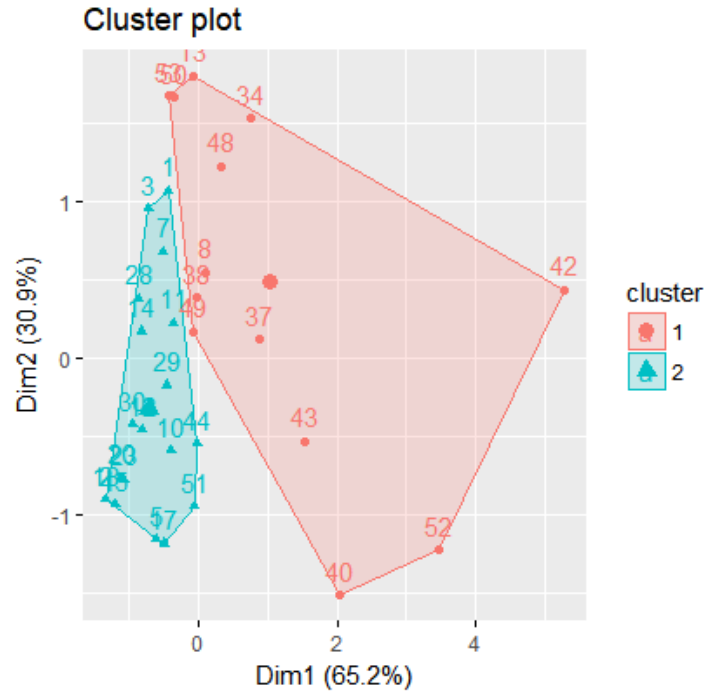


Figure 2-2 K-means clustering model results for $k=2$.

For $k=3$, the data was clustered as follows: cluster 1, 14 participants; cluster 2, 14 participants; cluster 3, 4 participants. The $k=4$ model clustered the data into 16, 6, 8 and 2 participants, respectively. Lastly, the $k=5$ model was an overfitting as well, with the clusters having 3, 12, 9, 2 and 6 participants, respectively. Our model $k=2$ clustered the dataset in the most appropriate way.

Figure 2-3 shows the final table that includes group assignment, cluster assignment, and CIA, AQ and EDE-Q scores. We converted the group values to number variables and then compared these values to the cluster assignment values. We created a confusion matrix, presented in Figure 2-4. We used this table to calculate our model's accuracy at 78.125% so we know our model is working well. Additionally, the Silhouette plot used to validate our model is shown in Figure 2-5. The dotted line represents the optimal number of clusters for this dataset, and we see that two clusters is the optimal solution.

	group	cluster	CIA_global	AQ	EDEQ_Global
1	control	1	0.03846154	0.8076923	0.008653846
2	control	1	0.00000000	0.3846154	0.000000000
3	control	1	0.00000000	0.7692308	0.003115385
5	control	1	0.03846154	0.3846154	0.027153846
7	control	1	0.03846154	0.7307692	0.010115385
8	control	2	0.23076923	0.7307692	0.013000000
10	control	1	0.07692308	0.5000000	0.024538462
11	control	1	0.07692308	0.6538462	0.016846154
12	control	1	0.03846154	0.5000000	0.011076923
13	control	2	0.11538462	0.9615385	0.005538462
14	control	1	0.03846154	0.6153846	0.003615385
17	control	1	0.07692308	0.3846154	0.027653846
18	control	1	0.00000000	0.3846154	0.000000000
20	control	1	0.03846154	0.4230769	0.003115385
23	control	1	0.03846154	0.4230769	0.004346154
28	control	1	0.00000000	0.6538462	0.003846154
29	clinical	1	0.03846154	0.5769231	0.021884615
30	clinical	1	0.00000000	0.5000000	0.009615385
34	clinical	2	0.19230769	0.9615385	0.032692308
37	clinical	2	0.38461538	0.6923077	0.031269231
38	clinical	2	0.23076923	0.6923077	0.010115385
40	clinical	2	0.50000000	0.4615385	0.082692308
42	clinical	2	1.00000000	1.0000000	0.129807692
43	clinical	2	0.42307692	0.6153846	0.060346154

Figure 2-3 The final output of our analysis. Table displays participant number, group assignment, cluster assignment, and CIA, AQ and EDE-Q scores.

```

cluster
numericGroup  1  2
1  11  5
2  2  14

```

Figure 2-4 Confusion matrix for the k-means clustering model.

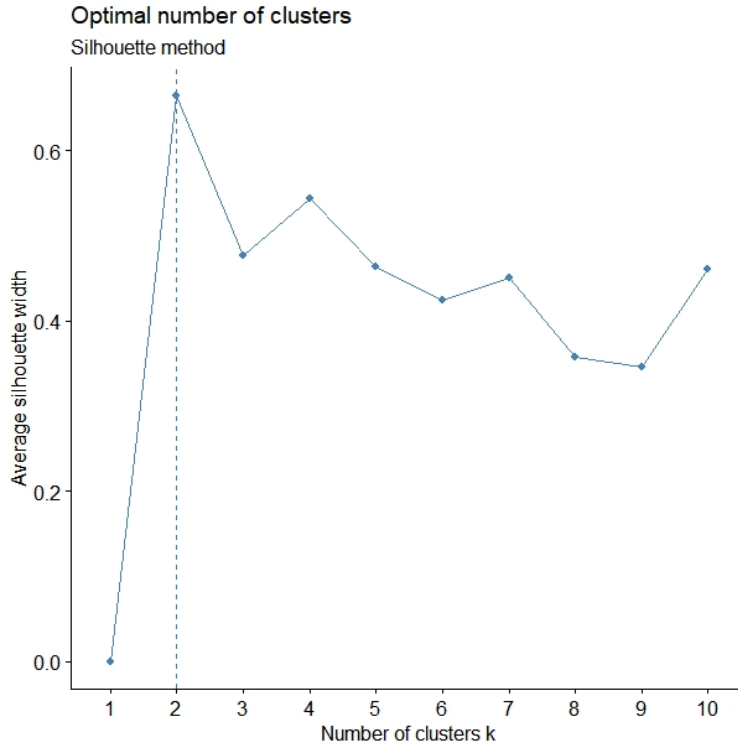


Figure 2-5 Plot of Silhouette Method showing the optimal number of clusters is 2.

2.3.2 Radar Plots

Once we determined that two clusters produced the optimal solution, we used the results and Excel to generate a radar plot representing the two clusters. This radar plot is shown in Figure 2-6. Because the EDE-Q, CIA, and AQ scores are calculated in different ways, the data needed to be scaled. A common practice is to scale between 0 and 1. However, we see in Figure 2-6 that the AQ score extremely skews the results. Therefore, we rescaled the data using z-scores and re-ran our analysis to have more interpretable results. The new radar plot is shown in Figure 2-7. Now that the scores are scaled more appropriately, we see that the EDE-Q and CIA scores are, in fact, important discriminators of eating disorder behavior.

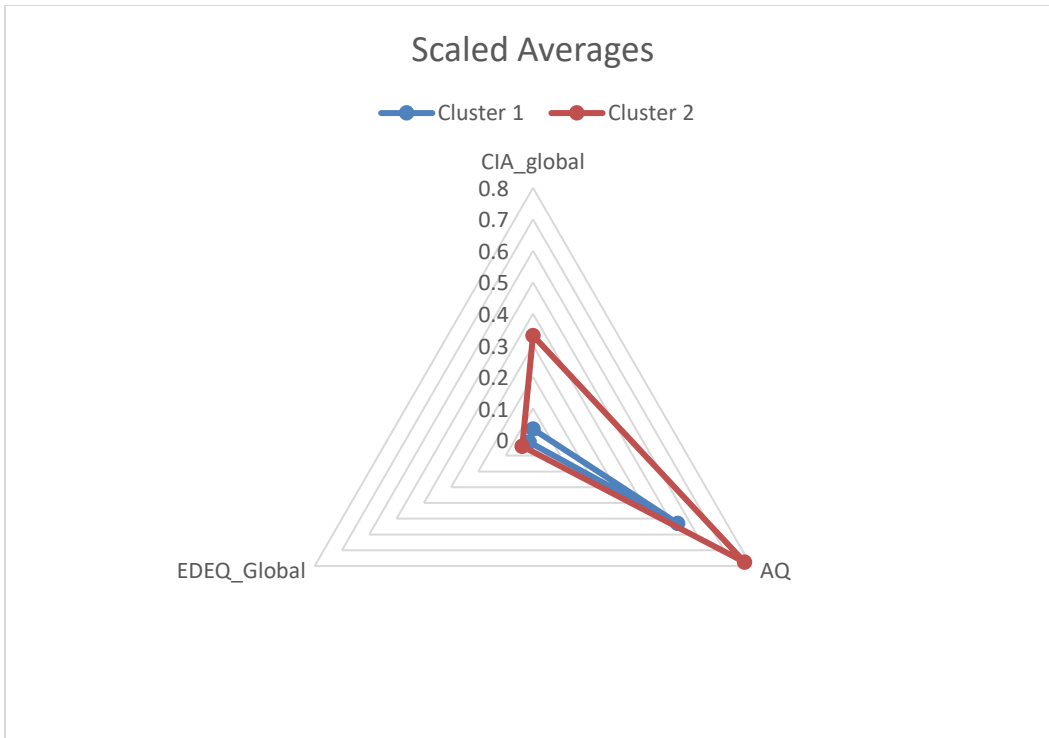


Figure 2-6 Radar plot of results when the data is scaled from 0 to 1.

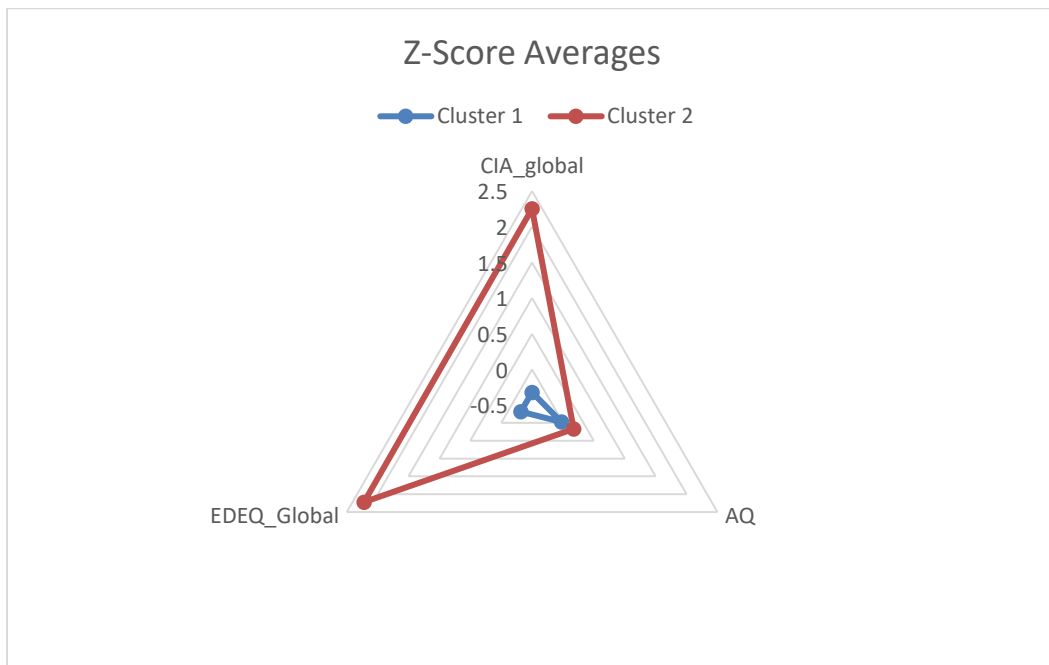


Figure 2-7 Radar plot of results when using z-score to scale the data.

Based on our truth data, we can determine that cluster 1 represents the control group and cluster 2 represents the clinical group. See Figure 2-3 to compare group assignment and cluster assignment. These groups are also shown in the radar plots by the blue and orange lines, respectively. We see that the clinical group is more driven by EDE-Q and CIA scores than the control group, which is to be expected due to the nature of the dataset.

2.4 Discussion

Our results prove that the EDE-Q and CIA are valid measures when determining eating disorder behavior, even though they are different types of diagnostic tools. Although each psychological test and measure has been tested for basic validity and accuracy before being adopted by professionals, there is not much research to date on whether these tests perform well with real-world datasets. Moreover, the medical field is quite subjective in the sense that each professional decides what resources to use when diagnosing patients. A professional may simply choose not to use certain diagnostic tools, even when they may give the best results. Alternatively, a professional may simply not know there is a better diagnostic tool than the one used. Therefore, it is imperative that researchers begin testing the efficacy of these tools in real-world settings. The analysis in this paper focuses on three of these tools, the EDE-Q, the CIA and the AQ.

We see a very strong association between the EDE-Q and CIA scores and cluster assignment. So, if we know a participant's EDE-Q or CIA score, we have a very good chance of assigning them to the correct group. What is interesting, and slightly unexpected, is that the EDE-Q and CIA scores influence the clusters in a very similar way. In fact, based on the radar plot in Figure 2-7, it would appear as though the two scores effect the clusters to the same degree. Certain implications may be drawn from this conclusion. For example, the CIA is not as costly as the

EDE-Q, the CIA is not a formal interview but rather a self-reported questionnaire, and the CIA is able to be completed in a shorter amount of time. For these reasons, the CIA may be a more viable option for teenage patients. Furthermore, if a professional only has access to the CIA and not the EDE-Q, he or she can be confident that the results are accurate and valid.

The dataset had some discrepancies that may have led to mixed results. For example, there were some participants in the control group who reported using disordered driven exercise to control their weight. Similarly, there were participants who reported binge eating, maintaining an unhealthy low weight, and even abusing diuretics to control weight. These are clearly eating disorder behaviors, yet the participants were part of the control group. This is likely because the disordered behavior was at a subclinical level, and therefore did not get diagnosed. Professionals must identify these outlying cases and determine if subclinical, yet still reportable, levels need to be considered.

We also scaled the data so that the AQ score would not skew the results, but supplementary research into the relationship between AQ score and eating disorder behavior is a necessary next step. It may be hypothesized that someone who scores higher on the AQ will also score higher on the EDE-Q and CIA, since these measures are indications of mental disorders and mental disorders often occur together. It is unfortunate that the original researchers did not offer any insight as to why they included the AQ score in their analysis [52], so at this point we cannot conclude if there is a connection between this dataset and the AQ measure. Regardless, the link between autism and eating disorder behavior is an interesting topic for additional research.

2.5 Conclusion

Eating disorders have become prevalent in our society, yet the research is still very mixed regarding why or how one develops this type of disorder. There are many factors that could play a role in manifestation, which means there is no one perfect treatment plan for all cases. In addition, eating disorders are often co-occurring with other disorders, which makes them more complex and not easily recognized or treated. Although more research has been conducted recently, deaths from eating disorders have continued and the rate of eating disorders does not seem to decrease despite better available therapies. It is critical that we begin to dissect this interesting cultural phenomenon, especially here in the United States.

This paper presented a novel approach to understanding eating disorder behavior by incorporating machine learning to an otherwise purely statistical field. With a final dataset of 32 participants, we employed a k-means clustering model to predict the optimal number of clusters to be two. Our results are easily confirmed by the truth data given in the dataset. We also employed the Silhouette method as a validation measure to justify our results. The EDE-Q and CIA scores seem to influence the results to the same degree, so the correlation of these two scores is a topic for future research. It is unclear after our analysis how AQ is related to eating disorder behavior, so additional research is certainly needed. This paper is but a small introduction into how machine learning can help detect and predict patterns in many types of psychological data.

3 Second Study: Analyzing Body Satisfaction via Clusters

3.1 Introduction

In recent years, the availability of robust machine learning-based computer vision and analysis techniques have provided new avenues for research in disciplines that have typically relied on classic statistics. In most cases, these machine learning approaches focus on building predictive classification (supervised) models, and not the cluster (unsupervised) models discussed here. However, we chose to explore an unsupervised model based on previous work that has established the utility of machine learning for tasks such as automated body analysis that takes imagery as input.

Kocabey and colleagues leveraged a computer vision system to understand the relationship between body mass index (BMI) as inferred from pictures uploaded on social media [118]. Results indicated not only that posters with lower BMI receive more “likes” on their profiles, but also that users with similar BMI tend to cluster together in social networks. Computer vision models were demonstrated to produce accurate predictions on BMI using basic face geometry in earlier work by Wen and colleagues, using simple machine learning techniques such as AdaBoost [119]. Later, it was further shown that textual data accompanying profile pictures can be used in addition with imagery data itself to accurately predict body weight and differentiate between individuals with healthy and non-healthy weights [120].

Most recently, state-of-the-art computer vision techniques have turned to deep learning to learn patterns from imagery data. This includes the application of deep convolutional neural networks (CNNs) to predict BMI with high accuracy from images [121]. To account for applications where the amount of data is small, the authors relied only on silhouettes extracted automatically from the raw images.

Our work here is not tied to algorithms that require body imagery as input data. Instead, we concentrate on numeric data as captured from user surveys. Rather than build a predictive model of any one concept, we instead emphasize the natural groupings of survey respondents using unsupervised cluster models. This presents yet another novel application of machine learning in addition to the vision-based approaches that have been explored previously.

3.2 Method

3.2.1 Unsupervised Learning

We completed this analysis using unsupervised learning as opposed to supervised learning. We focused on a technique known as hierarchical clustering, where data points are clustered together based on their similarity [102]. An unsupervised approach is particularly beneficial because researchers are not required to possess any prior knowledge of the dataset or even know of any patterns in the data [103]. Instead, the computer simply uses its own algorithm to deduce the optimal number of clusters for the dataset. Furthermore, unsupervised learning is often chosen for real-world data because researchers rarely, if ever, have access to correctly labeled data that can confirm the analysis results [103] [122]. Finally, hierarchical clustering provides more flexibility with real-world data [102]. For these reasons, we chose to use this type of clustering

model. We hypothesized that certain phenotypes would emerge from our analysis that would give us insight into who may show signs of body dissatisfaction.

3.2.2 Hierarchical Clustering

Initially, we hypothesized that using k-means clustering may have been sufficient. K-means is a top-down approach where the number of clusters desired (k) has to be decided on before running the algorithm [123]. It then selects random points in the data to be used as the centroid to each of those clusters. Once the centroid is selected, the algorithm splits the data into k clusters and recalculates the centroid points. It does this until the centroids do not change. For our purposes this approach is not very efficient because we do not know the optimal number of clusters prior to our analysis, nor do we want to decide the number of clusters prior to the analysis; rather, we want our algorithm to determine the number of clusters for us. Additionally, k-means splits the data evenly among the pre-selected number of clusters. This is another disadvantage in our case because we do not want to assume that all clusters are the same size. Hence, we opted to use hierarchical clustering.

In contrast to k-means clustering, hierarchical clustering is a bottom-up approach; every data point starts out as its own cluster [124]. The proximity score, or similarity score, between the vectors is calculated and the algorithm takes the two points with the minimum distance between them and combines those points to create a new cluster. This process is repeated until there is one cluster. The final clusters are determined by analyzing the dendrogram. A dendrogram is a tree representation formed while the program runs and it is used to interpret how the clusters were formed [125]. Whenever two points or clusters are combined, the dendrogram will join them with lines. The vertical lines represent the distance between the two clusters. The

dendrogram for our data can be seen in Figure 3-1. Usually, the threshold is set to cut through the tallest vertical line; in our case, we placed the threshold at 75. The final clusters are the number of vertical lines that are intersected by the threshold line. Therefore, we have four final clusters.

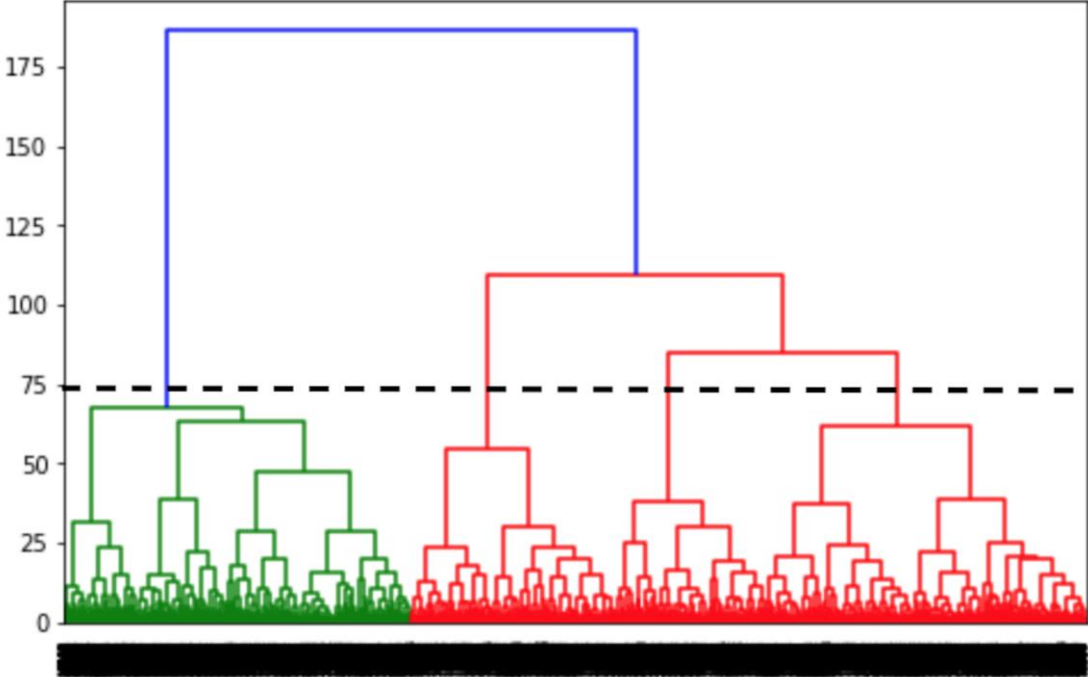


Figure 3-1 Dendrogram produced by our hierarchical clustering algorithm. The dotted line indicates the final four clusters.

3.2.3 Feature Selection

The original dataset consisted of six aggregate scores for each participant, however we see that there are only four aggregate scores used in our radar plots (Figure 3-2 and Figure 3-3).

Clustering was used to determine the features that are most differentiating across observations in the data, in particular the features that most clearly explain the latent structure in the underlying groups identified by the algorithm. The number of groups itself is determined quantitatively through the unsupervised learning process, typically through statistical measures. Here we

determined the number of clusters by examining the residuals of members in each cluster from their cluster mean and minimizing the sum of those residuals.

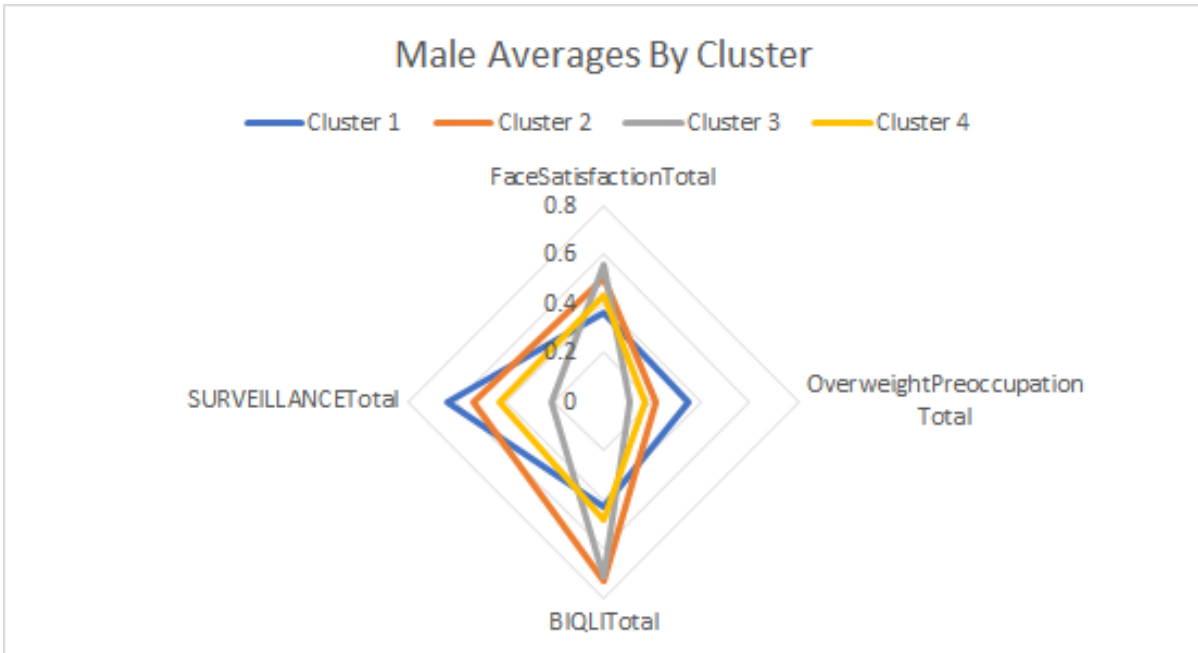


Figure 3-2 Radar plot for males with four final clusters.

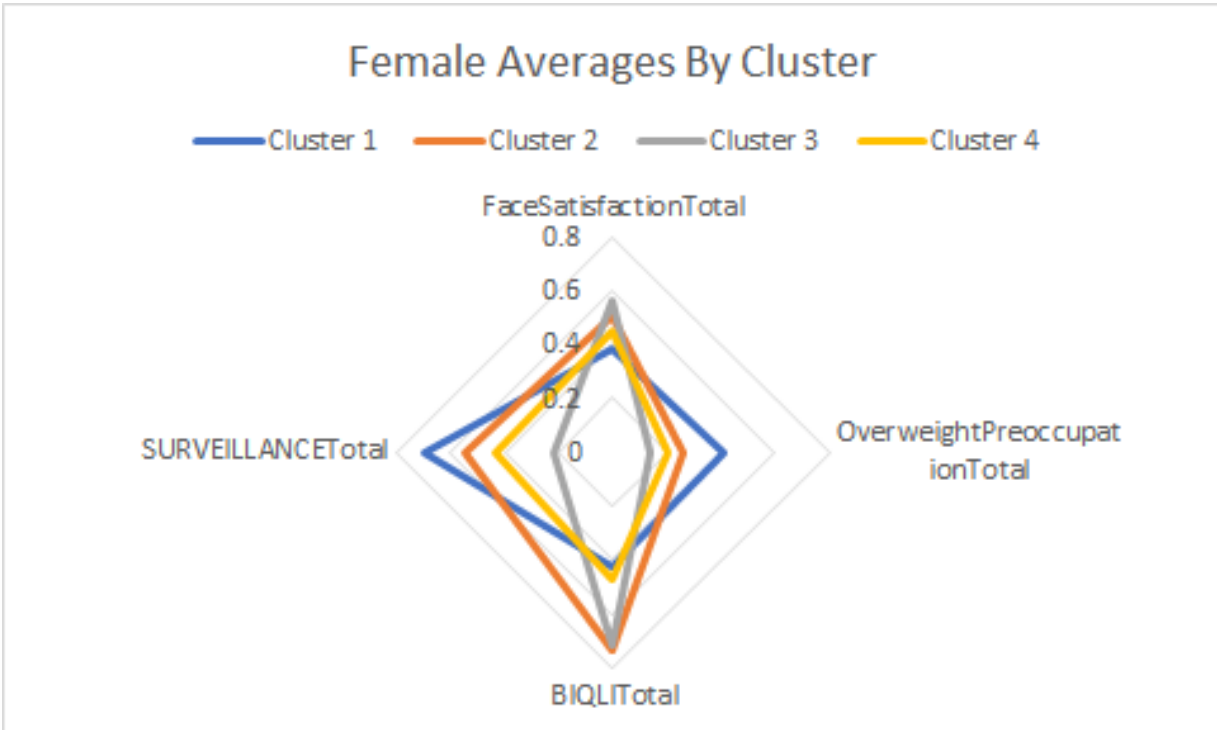


Figure 3-3 Radar plot for females with four final clusters.

3.2.4 Radar Plots

Once the hierarchical clustering model has determined the features that are most important and assigned a cluster to each participant, we used RStudio software and Excel to complete our analysis. The file that was created from our hierarchical clustering model included the following BIQLI aggregate scores, Surveillance aggregate scores, and Cluster. See Table 3-1 for reference. We normalized the aggregate scores from 0 to 1 so the results are easier to interpret, as well as merged the Sex column from our original dataset in order to separate these clusters based on this variable. See Table 3-2 for a snapshot of the final output file used. The averages were calculated for each cluster (Table 3-3 and Table 3-4) and presented as radar plots, seen in Figure 3-2 and Figure 3-3.

Table 3-1 This is a snapshot from the final output of our hierarchical clustering model algorithm. It is important to note that there are only four scores that remain in our output: Face Satisfaction, Overweight Preoccupation, BIQLI and Surveillance.

Participant	FaceSatisfaction Total	OverweightPre- occupationTotal	BIQLITotal	SURVEILLANCE Total	Cluster
0	5.00	1.00	5.95	2.50	2
1	4.00	3.00	4.21	4.38	3
2	4.75	3.00	4.16	3.00	3
3	3.00	1.75	3.89	2.50	3
4	4.00	2.00	5.00	5.00	1
5	4.25	1.00	3.68	1.38	2
6	4.00	1.00	3.84	2.25	2
7	3.75	3.50	5.05	2.88	2
8	5.00	5.00	7.00	4.13	1
9	5.00	3.00	7.00	2.50	2
10	2.00	2.50	3.21	4.13	0

Table 3-2 This is a snapshot from the final dataset. We merged the sex column from the original data file so that we can separate the dataset into males and females.

Sex	Cluster	FaceSatisfaction Total	OverweightPre- occupationTotal	BIQLITotal	SURVEILLANCE Total
0	2	0.67	0.00	0.83	0.25
0	3	0.50	0.33	0.54	0.56
0	3	0.63	0.33	0.53	0.33
0	3	0.33	0.13	0.48	0.25
0	1	0.50	0.17	0.67	0.67
0	2	0.54	0.00	0.45	0.06
0	2	0.50	0.00	0.47	0.21
0	2	0.46	0.42	0.68	0.31
0	1	0.67	0.67	1.00	0.52
0	2	0.67	0.33	1.00	0.25
0	0	0.17	0.25	0.37	0.52

Table 3-3 Table of scaled male average scores for each feature, used to produce the radar plot.

Feature	Cluster 1	Cluster 2	Cluster 3	Cluster 4
FaceSatisfactionTotal	0.36	0.50	0.56	0.43
OverweightPreoccupationTotal	0.35	0.22	0.11	0.17
BIQLITotal	0.43	0.74	0.71	0.48
SURVEILLANCETotal	0.64	0.53	0.21	0.42

Table 3-4 Table of scaled female average scores for each feature, used to produce the radar plot.

Feature	Cluster 1	Cluster 2	Cluster 3	Cluster 4
FaceSatisfactionTotal	0.38	0.51	0.56	0.45
OverweightPreoccupationTotal	0.41	0.26	0.14	0.20
BIQLITotal	0.42	0.73	0.72	0.47
SURVEILLANCETotal	0.70	0.55	0.22	0.43t

3.3 Results

Using RStudio software, we separated the dataset into males and females. First, we explored the summary statistics of each cluster with respect to BMI and age (Table 3-5 and Table 3-6) and used these results to compare clusters. As we have seen in previous research [126], though women had lower body satisfaction than men, the effect size was negligible (Table 3-5 and Table 3-6). Though there are no statistical differences between male and female groups, the shapes of the four clusters do provide interesting results and we will be concentrating on these clusters for the remainder of the paper. We present the clusters that were determined by our analysis (Figure 3-2 and Figure 3-3) and an explanation of the phenotypes that appear.

Table 3-5 Table of summary statistics for BMI and Age of male participants.

	BMI	Age
Cluster 1 Mean	29.48	31.69
Cluster 1 SD	6.27	8.99
Cluster 1 Median	28.48	30.00
Cluster 2 Mean	26.22	31.58
Cluster 2 SD	4.40	8.97
Cluster 2 Median	25.54	29.00
Cluster 3 Mean	26.60	35.68
Cluster 3 SD	5.05	11.19
Cluster 3 Median	25.54	33.00
Cluster 4 Mean	28.10	34.15
Cluster 4 SD	6.58	10.50
Cluster 4 Median	26.58	31.00

Table 3-6 Table of summary statistics for BMI and Age of female participants.

	BMI	Age
Cluster 1 Mean	29.66	33.85
Cluster 1 SD	7.17	10.57
Cluster 1 Median	28.34	31.00
Cluster 2 Mean	25.45	34.27
Cluster 2 SD	5.59	10.77
Cluster 2 Median	24.03	31.00
Cluster 3 Mean	26.58	38.25
Cluster 3 SD	6.36	11.92
Cluster 3 Median	25.01	35.00
Cluster 4 Mean	27.95	36.48
Cluster 4 SD	7.25	12.24
Cluster 4 Median	26.57	34.00

3.3.1 Clusters

Cluster 1 is Surveillance dominant. Surveillance refers to the participant’s self-monitoring of how he or she looks to others. Participants in this cluster agreed with statements such as, “During the day, I think about how I look many times,” and “I often worry about whether the clothes I am wearing make me look good.” Furthermore, participants in this cluster disagreed with statements like, “I rarely think about how I look,” and “I am more concerned about what my body can do than how it looks.”

Clusters 2 and 4 are BIQLI dominant, which specifically measures the relationship between body image to quality of life. Participants in these clusters felt that their appearance positively affected various areas of life. Additionally, participants in this cluster reported that their feelings of personal self-worth and adequacy positively affected their lives. Participants were asked about interactions with others, relationships with friends and family, and their overall satisfaction in

everyday life. We can see the hierarchical relationship between these two clusters in the radar plots, and we will explore this relationship further in the Discussion section of this paper.

Cluster 3 is Face Satisfaction and BIQLI dominant. Participants in this cluster are similar to Cluster 2 participants in that they felt appearance positively affected various areas of life. These participants also scored high in Face Satisfaction. For example, participants were asked to rate their happiness with the appearance of their face generally: “I am happy with the appearance of my face overall;” “I am happy with the shape of my face.” They were also asked to rate their level of happiness with specific parts of their face: “I am happy with the appearance of my nose;” “I am happy with the appearance of my eyes.” Participants in this group generally agreed with all of these statements. We expected to see this relationship in the data due to the positive nature of these variables; it makes sense that participants with a higher BIQLI score would also score high on the Face Satisfaction scale.

3.4 Discussion

The aim of this paper was to determine if there were any underlying patterns in the dataset using an unsupervised hierarchical clustering algorithm. We were not able to find any significant differences in survey responses when looking at males versus females, which seems to be in line with what other researchers have found [127]. However, our analysis was successful in showing clear differences in the four clusters we presented, and through these clusters we gained insight we previously have not had.

First, we now know that Surveillance, Face Satisfaction, BIQLI, and Overweight Preoccupation are critical features in the dataset. These features are used to group the participants in the most appropriate way, since these features are what determine the clusters. Next, we clearly see a

hierarchical relationship between the clusters, particularly clusters 2 and 4 (Figure 3-2 and Figure 3-3). Additionally, we saw in cluster 3 that the Face Satisfaction and BIQLI scores were positively associated with one another. This makes sense because higher scores on the Face Satisfaction and BIQLI scales indicate the participant has a positive body image. Finally, cluster 1 participants scored highest on the Surveillance scale, which may indicate that these participants experience body dissatisfaction.

In further research, it would be interesting to dissect the relationship between clusters 2 and 4 because there seems to be something going on that we cannot yet determine. Furthermore, it would be very beneficial to understand the characteristics of participants in clusters 2, 3 and 4 because they seem to be content with their body image. What is particularly thought-provoking, and potentially the biggest implication for future research, is in regard to cluster 1 participants. We know from previous research that people who experience body dissatisfaction also report greater dissatisfaction with life [127], among many other unfortunate circumstances. Thus, the link between Surveillance score and body dissatisfaction would be extremely noteworthy. We are not yet able to say that these two outcomes are correlated, but our results provide the necessary beginning for future researchers in this field.

4 Third Study: A Virtual Reality System for Practicing Conversation Skills for Children with Autism

4.1 Introduction

One in 59 American children is diagnosed with Autism Spectrum Disorder (ASD) [128]. While therapeutic supports exist (e.g., applied behavior analysis and cognitive-based therapy), they are costly and not always accessible due to geographic gaps in coverage or lack of available insurance funding. Assistive technology offers an alternative or supplementary approach to skill acquisition.

Children with ASD may experience difficulty with communication and behavior and often have social impairments [129] [130]. Many researchers have focused their studies on communication training to address such challenges [131] [132]. Some studies suggest that improved communication skills may lead to “improvements in daily living and social skills, and a reduction in behavior problems relating to social interactions for children with ASD” [129].

In the United States alone, researchers estimate that the total cost per year for a child with ASD is approximately \$17,000 more than for a child without ASD [133]. These costs include medical care for the children and special education programs and therapies, as well as accounting for loss in parent work productivity. Medical expenses for children with ASD are estimated to be 4.1–6.2 times greater than the expenses for those who do not have a diagnosis [134]. The current intervention paths, although effective, are often unattainable for families.

Assistive technology can offer a means to practice skills through an inexpensive, less time-consuming, and more scalable option. Not only can assistive technology help children by allowing them to practice lessons outside of therapy, but they may also help professionals by providing data regarding behavioral and communication skills. Therefore, we designed and implemented Bob's Fish Shop, a virtual reality (VR) environment to help children develop social and conversational skills while also providing the script output for professionals to study.

This paper presents the architecture of our system, which integrates gaze tracking and voice processing, in order to demonstrate the feasibility of building and using a VR-based assistive technology to help users with neurodiverse backgrounds to practice conversation skills. In addition to the design and development process, which sought input from both clinicians and caregivers, we also present the results of a technology probe in which we observed two children interact with our virtual environment. This process allowed us to gain additional insight into our system's affordances and usability, while at the same time underscoring the importance of a large-scale user study in the future to analyze efficacy.

4.2 Related Work

Previous work has addressed conversation skills by focusing on different aspects, such as: Joint attention that requires the user to attend to his or her virtual nonverbal behavior to complete an interaction [135]; turn-taking or reciprocity in the conversation that occurs through collaborative virtual reality systems and with robots [136] [137]; and etiquette practice through a single-user virtual environment [138].

One project that shares many of our same goals is MACH, My Automated Conversation Coach [139]. MACH is a system that provides social skills training through a virtual agent that

interviews the user. The virtual agent can read facial expressions and understand speech provided by the user through video and voice recognition. It is also able to respond in verbal and nonverbal manners. The recorded parameters for MACH include speaking rate, pitch variation, head movements, spoken words, loudness, and emphasis and pauses [139].

The sequence of events that takes place is simple. The virtual agent asks the user a question, the user responds, and then the virtual agent responds in an appropriate way based on the user's response. After the interview has finished, the system provides visual feedback of the scored parameters to allow the user to adjust his or her way of communicating.

It has been demonstrated by MACH [139] that practicing social skills in a safe and controlled environment helps users to better understand their social skill level, and they are more aware of areas requiring additional improvement. As mentioned earlier, ASD is often associated with social skill impairments as well as repetitive behaviors and restricted interests [25] [140].

Consequently, users with ASD may have trouble understanding appropriate speaking rate and volume [141] [142]. Furthermore, the issues in ASD go well beyond the targeted behaviors in MACH to include turn taking, greetings, and other social etiquette. Therefore, in this paper, we aim to expand on MACH's functionalities and hypothesize that users with ASD who engage in our unique virtual reality gaming experience can practice and improve their conversational understanding.

We chose a fish store game because the current research suggests that people diagnosed with ASD show significantly fewer challenges in social skills and behaviors when accompanied by pets, including dogs, hamsters, and cats [143] [144]. Furthermore, researchers have found that individuals with ASD show a strong interest in video games [145] and that video games can

successfully teach social skills [146] [147]. The assistive technology presented here, Bob's Fish Shop, combines the concept of developing a virtual gaming agent with animals to support social interactions.

4.3 Theory to Practice

With the abundance of ubiquitous computing systems available comes new opportunities to augment social information through sensor data as well as work around sensory experiences that are uncomfortable. Sensory processing differences in ASD may impact virtually every sensory system such as visual (sight), auditory (sound), vestibular (movement/orientation in space), olfactory (smell), proprioceptive (body awareness/pain) or tactile (pressure/touch). These differences have been characterized in ASD as an under- or over-sensitivity, also referred to hypersensitivity or hyposensitivity [148] [149]. For example, if an individual is hypersensitive to the smell of perfume, even the slightest amount may cause the individual to become ill. On the other hand, a person who may be hyposensitive to touch needs a tremendous amount of pressure or tactile reinforcement as compared to a typical individual. This is the premise we take with design and development of our technologies.

In recent years the availability of affordable, commercial-off-the-shelf VR hardware has also provided a catalyst for scalable, VR-based assistive technologies. This hardware includes self-contained headsets such as the Oculus Rift, HTC Vive, Samsung Gear, and Google Daydream Standalone. These headsets can interface with a variety of computing platforms and range in price, at the time of writing, from \$400-\$600 USD. More affordable options such as Google Cardboard, Google Daydream Smartphone, and Emerge Utopia range from \$15-\$99 USD but depend on a smartphone to provide the computational processing. Applications for these

platforms can be developed using standardized programming technologies such as Unity3D, Android SDK, and Swift, which further reduces barrier to entry when adopting these systems for assistive purposes.

Immersive VR offers new opportunities and challenges to directly modify sensory inputs. In immersive VR, the input for each of these systems can be removed, reduced, or manipulated to support the tolerance of sensory sensations in a therapeutic environment. Here we describe two immersive VR systems we built with emerging technologies and how we attuned them to the unique needs of people with ASD.

4.3.1 Bob's Fish Shop

Bob's Fish Shop is an immersive VR experience designed to help children with ASD practice typical social interactions and conversational skills. Implemented in Unity3D and designed for the Oculus Rift VR headset, the goal of Bob's Fish Shop is to build daily living skills while having children engage in a safe and supportive environment. In addition to conversational skills, the game exercises nonverbal communication and joint attention skills as well.

The premise of the game is simple. When players enter the virtual world, they are presented with an empty aquarium in their home. The goal is to incrementally add to the aquarium by adding fish, plants, and other accessories. Additionally, the player must tend to their fish, ensuring they are fed and well-cared for. Fish and supplies are acquired by visiting Bob's Fish Shop and interacting with Bob, the friendly animated shopkeeper (see Figure 4-1). Starting with a simple "Hello," Bob assists the user by asking them what they need and guiding them throughout the entirety of the interaction, giving both verbal and nonverbal cues as needed. The player's first-person perspective is used to gain insight into the presence of joint attention.

Throughout the game, tasks are laid in a left-to-right orientation to support sequencing of motor movements. This strategy promotes spatial awareness and motor planning. The narrator uses a wide range in pitch and emphasis when giving instructions to maintain attention and improve comprehension. Upon completion of their interaction with Bob, the user is returned to their home and rewarded with the items they explored at the fish shop.

Though the game play of Bob's Fish Shop is simple, based largely on short interactions supported by visual scripts, the underlying architecture of the game requires integration of several technologies. In addition to the VR itself, the game utilizes voice recognition, estimates joint attention based on the player's center of focus in the virtual world, and incorporates rule-based artificial intelligence to guide transitions throughout the game.

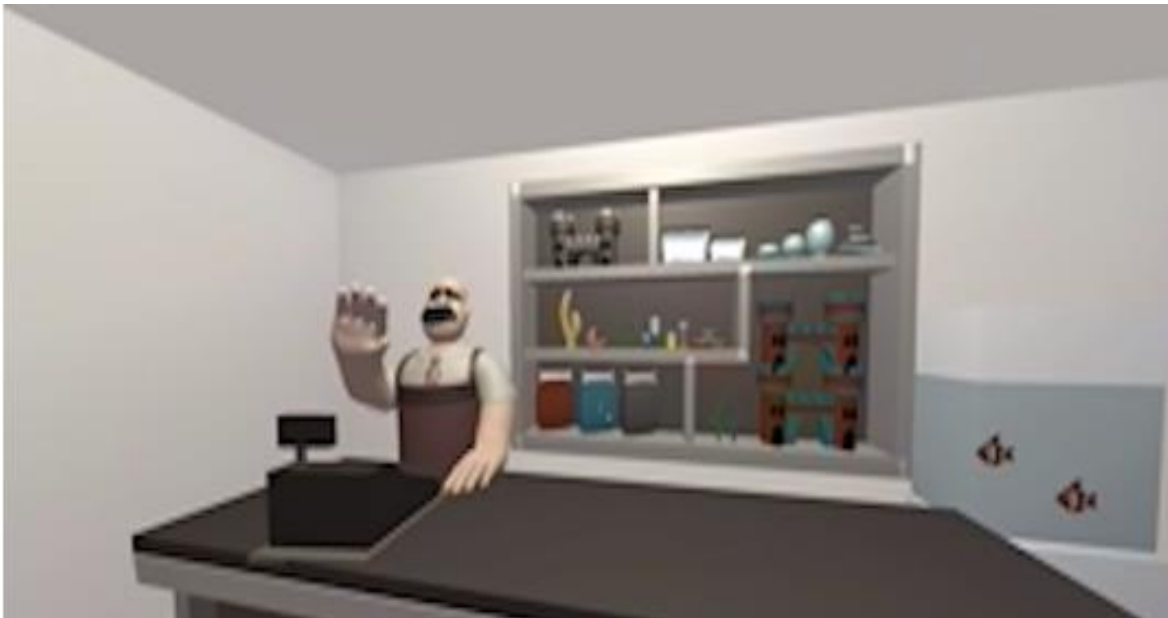


Figure 4-1 Bob's Fish Shop: Screenshot of shop owner greeting the VR user.

4.3.2 VirtualBlox

In addition to the availability of consumer-grade and moderately priced VR headsets, the development of sensors that allow gesture recognition and visual feedback to be integrated into

immersive experiences have expanded the types of interactions users can have within a virtual world. VirtualBlox is an immersive VR game built for the Oculus Rift. VirtualBlox is designed to exercise fine and gross motor skills, which often children diagnosed with ASD experience.

The game makes use of the LeapMotion hand-tracking sensor and API to allow the user to manipulate objects in the virtual world. In the case of VirtualBlox, the user may select from several sorting exercises which prompts them to place or stack blocks in predetermined locations. This not only requires gross motor planning on behalf of the user, but also fine motor skills to grasp individual blocks and release them in the correct positions, as depicted in Figure 4-2.

Visual feedback provides the user with indications of whether they have correctly sorted individual blocks, and the user may choose between a variety of timed and untimed exercises. Additionally, the appearance of the blocks may be customized through texture-mapping files, making it possible to alter the experience to align with the interests of the user. For example, a child interested in Pokémon can easily be presented with blocks representing their favorite characters.



Figure 4-2 Screenshot of VirtualBlox block sorting game.

4.4 Technology: Bob's Fish Shop System

Bob's Fish Shop is an immersive virtual reality experience designed to help children with ASD practice typical social interactions and conversational skills. Implemented in Unity 3D and designed for the Oculus Rift VR headset (Figure 4-3), the goal of Bob's Fish Shop is to develop social and conversational etiquette while having children engage in a safe and supportive environment. In addition to verbal conversation, the game provides opportunities to practice nonverbal communication, such as responding to waving (Figure 4-4), and joint attention skills, such as referencing a person or an object of shared interest with the eyes. Video demonstrations of the system are available on the web here: <https://github.com/mlat/vrpaper>.



Figure 4-3 The Oculus Rift headset and microphone used for voice input.



Figure 4-4 Image of Bob making eye contact with user.

Though the game play of Bob's Fish Shop is simple, based largely on short interactions supported by text scripts, the underlying architecture of the game requires integration of several technologies. In addition to the VR itself, the game utilizes voice recognition to engage the user and the virtual shopkeeper, estimates joint attention based on the player's center of focus in the virtual reality environment (VRE), and incorporates rule-based artificial intelligence to guide transitions throughout the game.

4.5 System Development

We conceptualized the system based on the experiences of the research team, which includes a Board-Certified Behavior Analyst (BCBA) with 20 years of clinical experience. Additionally, behavior interventionists from a local ASD treatment clinic were consulted in order to design a virtual reality scenario that would be appealing to our target audience. This resulted in a simple scenario based on the interaction required for a person to successfully interact with the proprietor of a pet shop. We then devised system requirements from previous empirical work and from our concept in order to build the system. As currently built, the game leverages Maya (drawing software), Unity, C# scripting, and an external voice recognition software.

4.5.1 Scenario

The user begins in their virtual home and then leaves their virtual home to enter the virtual fish shop. Once the user has entered the shop, they examine the contents of the shelves and gain an idea of items they would like to purchase. They then engage the shopkeeper, Bob, with their gaze, signaling they are ready for a social interaction. Bob waves, then introduces himself, and offers his assistance to the customer in the shop, the user. Bob and the user then have a conversation regarding which items they would like to purchase in the shop.

We chose this use case because this type of conversation happens every day. For example, whether one is at a store purchasing items, at a restaurant ordering dinner, or at home telling a parent or caretaker what they would like to do the upcoming weekend, the applications of this particular social interaction are endless. Having the ability to express one’s needs and desires is a skill used every day.

4.5.2 Implementation

The VRE comprises five primary software modules: Staging script, vision processing script, voice processing script, data archive script, and character animations. A diagram of the software is shown in Figure 4-5.

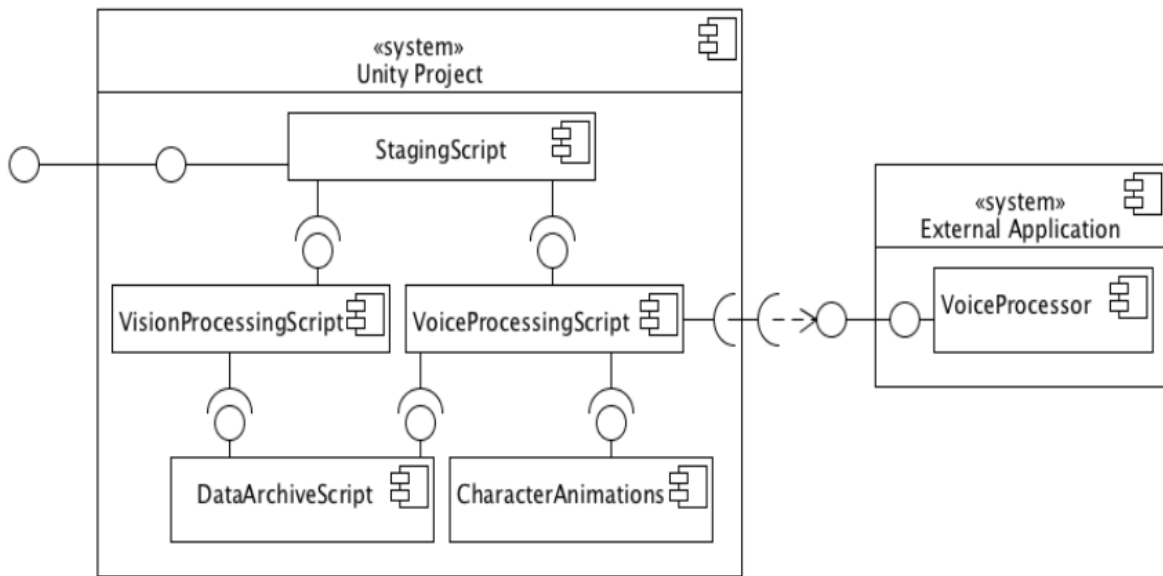


Figure 4-5 Diagram of the software components for Bob’s Fish Shop.

The staging script component handles each of the possible stages that could be in the current social interaction. It is also able to call the visual processing script component and the voice

processing script component to receive information from the user based on their vision and voice inputs.

The vision processing script component tracks where the user is looking. This is then documented in the form of a text file, so professionals can observe where the user was looking (i.e., in the expected place for a given exchange). An example of the output is presented in Figure 4-6.

Within the voice processing script component, the system calls an external application that processes the user's voice and sends the translated text back to the voice processing script component. The external voice-to-text application runs locally as a web service on the same physical machine as the other system components and is easily invoked using standard C# capabilities. Because the responsiveness of the system is critical for the user experience, no additional pre-processing is carried out on the audio received by the user. Instead, we make use of an industry-grade microphone to capture audio, which we have found to produce good enough results in practice that further audio cleanup is not necessary. Once the process is complete, the voice processing component can then parse the text and communicate which stage to transition to back to the staging script component.

The data archive script component documents data that are valuable from the interaction between the user and Bob. The information is transferred to this component from the vision processing script and the voice processing script.

The character animations component, which controls the shopkeeper's movements and actions throughout the scene, uses the trigger from the voice processing script and performs the appropriate animations based on the user's response.

```
**Conversation Starts**  
Bob: Hello. What would you like to buy from my shop?  
**User is looking at Bob**  
User: Can I have a blue fish please?  
**User took 6 seconds to respond**  
Bob: Sure! Is this the item you would like to buy?  
**User is looking at the blue fish**  
User: Yes.  
**User took 2 seconds to respond**  
Bob: Great! Would you like to buy anything else?  
**User is looking at the door**  
User: No.  
**User took 3 seconds to respond**  
Bob: Ok. Thank you for shopping at my fish shop!  
**User is looking at Bob**  
**Conversation Ends**
```

Figure 4-6 Sample of system output.

4.6 Functionality

The basic functionalities that the user can do are: Walk into the room, look around the room, and communicate through voice to converse with Bob. With the use of the Oculus Rift SDK, we integrated Unity with Oculus functionalities. By replacing the main camera in the scene with a camera provided by the Oculus SDK, the user can move around the scene as if they were inside the virtual reality world.

Being able to track eye contact was a priority for this project. Tracking the location of the user's eyes in the scene allows the software to record where the user's visual attention is during the span of the conversation.

Since a conversation with Bob is the main functionality of this software, we recorded many variations of this interaction. In consultation with a BCBA, we created a baseline script, which mapped out an example conversation that the user and Bob could have at his store. Then, a few other variations of those phrases were made to prevent unnatural repetition during the conversation. When all of Bob's possible lines were created for the baseline example, a professional voice artist recorded all of the lines in a studio and a voice engineer cleaned up the recordings so we could use each individual line in our Unity project.

Once the voice recording files were clean and ready to be used in the scene, the digital artist animated Bob's mouth and body expressions to make it seem like he was speaking the words on the voice recordings. The eye contact scripts were also applied to Bob. The figures and animations were then added into the Unity project so the items in the shop were actual objects in the scene.

After the animations and 3D digital figures were added to the scene and the appropriate scripts were attached to trigger those animations, the different conversation stages were added. The staging script component in Unity handled the transitions from one part of the conversation to another. Based on the user's responses to Bob's interactions, the script either transitions out of the stage it is in, or it repeats the current stage.

During each of these stages, the voice processing script component collects speech from the user and processes it to determine what sequence of events should happen throughout the game.

Within each stage class, an external application is called to pick up the voice of the user as an input. Then, using a voice recognition library, the user's voice is translated into text and sent back to the Unity software to be processed. The full statements said by the user are then recorded to a text file to be analyzed by parents and professionals using the data archive script component.

After that text is printed to the file, it is parsed for specific hot words that lead to the transitioning of the conversation. Some of these hot words include "food", "castle", "red fish", "blue fish", "yes", and "no". Over time, as the user continues to interact with the virtual world, their use of specific words is used to probabilistically determine the response received from Bob. This provides a simple mechanism for adding variety to the interactions in the system as well as encouraging the user to try different approaches in their conversation with Bob.

While this process is occurring, a timer is keeping track of how long it takes the user to respond to Bob. The time is also recorded to the text file. An example of the final format of the output looks like Figure 4-6.

4.7 System Validation

In order to provide basic validation of our system, we carried out a small technology probe with potential users. Our technology probe was inspired by the method founded by Hutchinson and colleagues [150], in which we tested our design and received feedback from our users. The user study consisted of one exploratory session, conducted in a university research lab. Two children participated in the user study, a six-year-old female diagnosed with ASD and a seven-year-old

male diagnosed with Attention Deficit Hyperactivity Disorder (ADHD). The children were accompanied by their mothers, for supervision as well as to assist in the data collection process.

4.7.1 Data Collection

The children were immersed in the VRE for approximately 15 nonconsecutive minutes. During the study, each user wore the headset to navigate through Bob's Fish Shop, and they were able to communicate to one another as well as to their mothers during their experience. Throughout the duration of the study, data were collected through observation and interview questions. Interview questions included: "What do you see?" and "What are you looking at?"

4.7.2 Analysis

Once the user study was completed, researchers collected and examined all field notes and interview questions using a qualitative approach. Open coding [151] and discussions among the researchers were used to discover the emergent themes specific to the system. The main focus was to determine the feasibility and acceptability of our system in the ASD community.

4.8 Results

The study was a positive experience for the users, and minimal training was required to use the VR headset. The users quickly discovered the immersive nature and malleability of the system, while also interacting socially in the physical world.

4.8.1 Immersive

We specifically designed the VRE to be similar to cartoon animations because we wanted the characters and gestures to be familiar to the users.

“Wow, it’s like being in a cartoon!” (s1, child with ASD)

The primary use of a VR headset is to immerse the user completely in a new virtual world separate from our physical world, and it was evident that the user easily remained engaged because of this design. The users also expressed their surprise at how interesting and fun Bob’s Fish Shop was, and they wanted to continue the session beyond the 15 minutes. Furthermore, our results were congruent with other recent studies in that cybersickness was not a concern with the Oculus Rift VR headset, and the users reported a pleasant experience [152] [153].

4.8.2 Malleable

An important aspect to VREs is the ability to create whatever type of environment you want. Interestingly, the children recognized this feature early into the study. For example, while the female child enjoyed the idea of picking out fish, the male child wanted to change the scenario to something else.

“Could it be a pet store with cats?” (s2, child with ADHD)

“Can I draw a dragon in Bob’s Fish Shop?” (s2, child with ADHD)

This understanding demonstrates how the details of the VRE are trivial. The social interaction is the key to this technology supporting social skill development. The details are simply a way to engage the user for the entire session.

4.8.3 Social Reciprocation

An emergent theme that was not anticipated prior to this study was the social exchange between the users outside of the VRE. One key objective to our technology is social skill acquisition

through the user's engagement in Bob's Fish Shop. However, we were excited to see that social skills were immediately exercised through turn-taking in the physical world as well.

"Tell me what you see." (s2, child with ADHD)

"When is it my turn again?" (s1, child with ASD)

Because the VR headset can be easily taken on and off, the users were able to switch off after every few minutes during the session. This also allowed them to communicate their experience to each other as well as to their mothers.

4.9 Implications for Future Practice

As shown above in Figure 4-6, the three behaviors that are being recorded are: Where the user is looking throughout the span of the conversation, how long it takes for the user to respond to Bob, and the verbal exchanges between the two.

More specifically, we designed the system to detect where the child is looking throughout the conversation in order to measure attentiveness as well as how easily distracted the child is while the interaction is taking place. The system records the length of time (in seconds) it takes for the child to respond to Bob during the conversation in order to measure how long the child is paying attention. We captured the transcript to determine if the child understood what took place during the conversation and how decisive the child was during this spontaneous interaction.

This information can be reviewed and analyzed by the user, family, and professionals. The transcript guides therapists and parents to which areas that child needs more focus. For example, if it takes a child six seconds to respond to a question from Bob, then the child needs to work on

delivering a quicker response. Similarly, if a child is looking at a red fish but wants to purchase fish food, then the child needs help with focused attention.

Children may also be able to see their own successes and mistakes through the text conversation. The user's progress can be tracked over time to see which areas have improved and which areas still need focus. Parents and therapists can review the text with the child and point out more appropriate behaviors and/or responses, promoting a positive and informative learning environment.

While our technology probe proved to be incredibly useful as a basic validation of our system's architecture, it is important to emphasize that this is not sufficient to draw any conclusions regarding the efficacy of the system in improving conversational skills. This requires a more formal user study with a much larger sample size, including users with both neurotypical and neurodiverse backgrounds. As such, the primary contribution of this paper is the technical development of the system, with the goal of providing a rigorous analysis of outcomes in our future work.

4.10 Conclusions

VR enables the creation of information-rich environments that are tolerable for people with sensory sensitivities. However, the richness of the information must be balanced between the attention and energy required to manage it. VR, particularly fully immersive VR, offers an intense sensory experience, far beyond that of a traditional screen-based interaction. Neurodiverse individuals often struggle with sensory input [154]. Thus, a primary advantage to hosting an intervention in VR is the ability to control the sensory load in the system, adapting it to meet the sensory needs of the individual.

Immersive VR allows for customized interactions, such that individuals can attend classrooms with their own individualized input settings or other kinds of experiences without sharing a sensory space. The flexibility of controlling the sensory environment opens opportunities to be more inclusive. By designing a space that is tailored to individual needs (e.g., ADHD, ASD, Sensory Processing Disorder, Post-Traumatic Stress Disorder, etc.), more people can participate in virtual face-to-face interactions and other cultural experiences.

This paper presents a virtual reality environment, Bob's Fish Shop, which provides opportunities for users with neurodiverse backgrounds to develop necessary conversation skills in a safe and controlled environment. We effectively demonstrated that our VRE is an acceptable, feasible system that engaged our users and promoted social conversation by carrying out a technology probe with a small sample of two users. Future studies will explore whether the VR technology presented in this paper supports social skill development through a large user study. It would also be interesting to expand this VRE to a collaborative multiuser virtual environment, similar to those found in recent studies [155] [156]. Finally, we would like to test our hypothesis that users with ASD who study their script outputs from this virtual reality gaming experience will notice mistakes and improve their conversational understanding. It is clear, now more than ever, that the human species is diverse and our needs are different, including our sensory needs.

Traditionally, our system (professionally, educationally, therapeutically) has been a one size fits all model. However, VR allows us to customize a unique experience, considering each individual's needs, abilities, and preferences.

5 Conclusion

In this dissertation, we explored three areas of psychology: eating disorders, body satisfaction, and ASD. To date, there is relatively little, or even no, research on these topics using machine learning. I, along with my colleagues, saw a unique opportunity to conduct research on these topics using various machine learning algorithms. This dissertation was separated into two sections. The first section is comprised of chapters 2 and 3, which focus on using hierarchical clustering algorithms for eating disorder and body image datasets. The second part is dedicated solely to ASD and assistance through VR.

Chapter 2 presents a dataset on eating disorder behaviors, specifically individuals with a history of AN, which is a very complicated disorder. Due to the variability in diagnosis and symptoms, treatment is unique and there are numerous assessment tools available. We used a semi-supervised k-means clustering technique to explore the EDE-Q, CIA, and AQ scores. We can conclude, based on our k=2 model, that the EDE-Q and CIA scores are important discriminators of eating disorder behavior. This is particularly useful for practitioners because our results show that two different types of assessment tools perform equally well.

Chapter 3 is an extension of our first study in that body image and satisfaction is directly correlated with eating disorder behavior. In other words, if you have lower body satisfaction then you will be more likely to develop an eating disorder. We employed a hierarchical clustering algorithm to determine four unique clusters in our dataset. Cluster 1 was Surveillance dominant, Clusters 2 and 4 were BIQLI dominant, and Cluster 3 was Face Satisfaction and BIQLI

dominant. Participants in Cluster 3 had very positive body image. Furthermore, it is possible that the individuals in Cluster 1 are the individuals more likely to develop an eating disorder, but more research is needed before this conclusion can be made.

Chapter 4 explores ASD and VR. Specifically, we describe the ways to address sensory differences to support neurologically diverse individuals by leveraging advances in VR. ASD can impact social, cognitive, and communication skills; VR provides assistance for these diverse sensory perceptual abilities. Additionally, we can create an opportunity to improve the interactions people have with technology and the world. We introduce virtual environments that support variations in sensory processing.

Chapter 4 also describes a virtual reality environment, Bob's Fish Shop, which provides a VR system particularly for users diagnosed with ASD. Users can practice social interactions in a safe and controlled environment. We present a case study which suggests such an environment can provide the opportunity for users to build the skills necessary to carry out a conversation without the fear of negative social consequences present in the physical world. Through the repetition and analysis of these virtual interactions, users can improve social and conversational understanding.

Psychology is a new field and it is only becoming more expansive as time goes on. With the assistance of machine learning algorithms, we will be able to understand the human experience like never before. The more we understand the human experience and brain functionalities, the better we can build and develop computers. Computers and machine learning algorithms are, after all, modeled after human intelligence.

Assistive technology allows people with disabilities to become more able to complete tasks that would be difficult to do without the assistive technology. Individuals with ASD exhibit deficits in many areas of life. VR allows people with ASD to accomplish a lifestyle that would be challenging without the assistive technology, both as a child in a classroom and as an adult in society.

In conclusion, the study of psychological topics with machine learning is imperative for all disciplines to advance in the future. Studying these topics through the lens of machine learning offers us a new perspective. Instead of using basic statistical models to explain the data, we utilize machine learning to dive deeper into the underlying patterns and relationships. In addition, machine learning algorithms allow researchers to predict future behavior and the models become more accurate over time.

References

- [1] S. K. Ciccarelli and J. N. White, *Psychology*, Upper Saddle River, New Jersey: Pearson Education, Inc., 2009.
- [2] E. Linstead, D. R. Dixon, R. French, D. Granpeesheh, H. Adams, R. German, J. Kornack et al., "Intensity and Learning Outcomes in the Treatment of Children with Autism Spectrum Disorder," *Behavior Modification*, vol. 41, no. 2, pp. 229-252, 2017.
- [3] E. Linstead, D. R. Dixon, E. Hong, C. O. Burns, R. French, M. N. Novack and D. Granpeesheh, "An Evaluation of the Effects of Intensity and Duration on Outcomes Across Treatment Domains for Children with Autism Spectrum Disorder," *Translational Psychiatry*, vol. 7, no. 9, pp. e1234-e1234, 2017.
- [4] K. K. Hyde, M. N. Novack, N. LaHaye, C. Parlett-Pelleriti, R. Anden, D. R. Dixon and E. Linstead, "Applications of Supervised Machine Learning in Autism Spectrum Disorder Research: A Review," *Review Journal of Autism and Developmental Disorders*, vol. 65, no. 2, pp. 128-146, 2019.
- [5] D. R. Dixon, E. Linstead, D. Granpeesheh, M. N. Novack, R. French, E. Stevens, A. Powell et al., "An Evaluation of the Impact of Supervision Intensity, Supervisor Qualifications, and Caseload on Outcomes in the Treatment of Autism Spectrum Disorder," *Behavior Analysis in Practice*, vol. 9, no. 4, pp. 339-348, 2016.
- [6] E. Stevens, D. R. Dixon, M. N. Novack, D. Granpeesheh, T. Smith and E. Linstead, "Identification and Analysis of Behavioral Phenotypes in Autism Spectrum Disorder Via Unsupervised Machine Learning," *International Journal of Medical Informatics*, vol. 129, pp. 29-36, 2019.
- [7] E. Hong, D. R. Dixon, E. Stevens, C. O. Burns and E. Linstead, "Topography and Function of Challenging Behaviors in Individuals with Autism Spectrum Disorder," *Advances in Neurodevelopmental Disorders*, vol. 2, no. 2, pp. 206-215, 2018.
- [8] E. Stevens, A. Atchison, L. Stevens, E. Hong, D. Granpeesheh, D. Dixon and E. Linstead, "A Cluster Analysis of Challenging Behaviors in Autism Spectrum Disorder," 2017.
- [9] D. R. Dixon, C. O. Burns, D. Granpeesheh, R. Amarasinghe, A. Powell and E. Linstead, "A Program Evaluation of Home and Center-Based Treatment for Autism Spectrum Disorder," *Behavior Analysis in Practice*, vol. 10, no. 3, pp. 307-312, 2017.

- [10] E. Linstead, R. German, D. Dixon, D. Granpeesheh, M. Novack and A. Powell, "An Application of Neural Networks to Predicting Mastery of Learning Outcomes in the Treatment of Autism Spectrum Disorder," in *IEEE 14th International Conference on Machine Learning and Applications (ICMLA)*, 2015.
- [11] E. Linstead, R. Burns, D. Nguyen and D. Tyler, "AMP: A Platform for Managing and Mining Data in the Treatment of Autism Spectrum Disorder," in *38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2016.
- [12] K. Hyde, A. J. Griffiths, C. Giannantonio, A. Hurley-Hanson and E. Linstead, "Predicting Employer Recruitment of Individuals with Autism Spectrum Disorders with Decision Trees," in *17th IEEE International Conference on Machine Learning and Applications*, 2018.
- [13] L. Stevens, D. Kao, J. Hall, C. Görg, K. Abdo and E. Linstead, "ML-MEDIC: A Preliminary Study of an Interactive Visual Analysis Tool Facilitating Clinical Applications of Machine Learning for Precision Medicine," *Applied Sciences*, vol. 10, no. 9, p. 3309, 2020.
- [14] N. S. Rosenfield and E. Linstead, "A Cluster Analysis: Exploring the Eating Disorder Examination Questionnaire, Clinical Impairment Assessment and Autism Quotient to Identify Eating Disorder Vulnerability," *Machine Learning and Knowledge Extraction*, no. In Review., 2020.
- [15] N. S. Rosenfield, E. Eiroa, E. Linstead and D. Frederick, "Analyzing Body Satisfaction via Clusters," *In Preparation*.
- [16] N. S. Rosenfield, K. Lamkin, J. Re, K. Day, L. Boyd and E. Linstead, "A Virtual Reality System for Practicing Conversation Skills for Children with Autism," *Multimodal Technologies and Interaction*, vol. 3, no. 2, p. 28, 2019.
- [17] L. E. Boyd, K. Day, N. Stewart, K. Abdo, K. Lamkin and E. Linstead, "Leveling the Playing Field: Supporting Neurodiversity Via Virtual Realities," *Technology & Innovation*, vol. 20, no. 1, pp. 105-116, 2018.
- [18] H. R. Millar, F. Wardell, J. P. Vyvyan, S. A. Naji, G. J. Prescott and J. M. Eagles, "Anorexia Nervosa Mortality in Northeast Scotland, 1965–1999," *American Journal of Psychiatry*, vol. 162, no. 4, pp. 753-757, 2005.
- [19] S. Zipfel, B. Löwe, D. L. Reas, H. C. Deter and W. Herzog, "Long-Term Prognosis in Anorexia Nervosa: Lessons From a 21-Year Follow-Up Study," *The Lancet*, vol. 355, no. 9205, pp. 721-722, 2000.
- [20] F. R. E. Smink, D. van Hoeken and H. W. Hoek, "Epidemiology of Eating Disorders: Incidence, Prevalence and Mortality Rates.," *Current Psychiatry Reports*, vol. 14, p. 406–414, 2012.

- [21] American Psychiatric Association, *Feeding and Eating Disorders : DSM-5® Selections*, American Psychiatric Association Publishing, 2016.
- [22] P. F. Secord and S. M. Jourard, "The Appraisal of Body-Cathexis: Body-Cathexis and the Self," *Journal of Consulting Psychology*, vol. 17, no. 5, p. 343, 1953.
- [23] R. M. Lerner and S. A. Karabenick, "Physical Attractiveness, Body Attitudes, and Self-Concept in Late Adolescents," *Journal of Youth and Adolescence*, vol. 3, pp. 307-316, 1974.
- [24] E. G. Rounds and L. A. Stutts, "The Impact of Fitspiration Content on Body Satisfaction and Negative Mood: An Experimental Study," *Psychology of Popular Media*, 2020.
- [25] American Psychiatric Association, *Diagnostic and Statistical Manual of Mental Disorders (DSM-5®)*, American Psychiatric Pub., 2013.
- [26] J. M. Maenner et al., "Prevalence of Autism Spectrum Disorder Among Children Aged 8 Years — Autism and Developmental Disabilities Monitoring Network, 11 Sites, United States, 2016," *MMWR Surveillance Summaries 2020*, vol. 69, no. No. SS-4, pp. 1-12.
- [27] A. M. Donnellan, D. A. Hill and M. R. Leary, "Rethinking Autism: Implications of Sensory and Movement Differences For Understanding and Support," *Frontiers in Integrative Neuroscience*, vol. 6, no. 124, pp. 1-11, 2013.
- [28] S. M. Robertson, "Neurodiversity, Quality of Life, and Autistic Adults: Shifting Research and Professional Focuses Onto Real-Life Challenges," *Disability Studies Quarterly*, vol. 30, no. 1, 2009.
- [29] J. Sinclair, "Don't Mourn For Us," 1993.
- [30] T. Owren and T. Stenhammer, "Neurodiversity: Accepting Autistic Difference," *Learning Disability Practice*, vol. 16, no. 4, pp. 32-37, 2013.
- [31] R. R. Ahn, L. J. Miller, S. Milberger and D. N. McIntosh, "Prevalence of Parents' Perceptions of Sensory Processing Disorders Among Kindergarten Children," *American Journal of Occupational Therapy*, vol. 58, no. 3, pp. 287-293, 2004.
- [32] B. C. Love, "Comparing Supervised and Unsupervised Category Learning," *Psychonomic Bulletin & Review*, vol. 9, no. 4, pp. 829-835, 2002.
- [33] S. B. Kotsiantis, I. Zaharakis and P. Pintelas, "Supervised Machine Learning: A Review of Classification Techniques," *Emerging Artificial Intelligence Applications in Computer Engineering*, vol. 160, no. 1, pp. 3-24, 2007.

- [34] R. Sathya and A. Abraham, "Comparison of Supervised and Unsupervised Learning Algorithms For Pattern Classification," *International Journal of Advanced Research in Artificial Intelligence*, vol. 2, no. 2, pp. 34-38, 2013.
- [35] S. C. Johnson, "Hierarchical Clustering Schemes," *Psychometrika*, vol. 32, no. 3, pp. 241-254, 1967.
- [36] F. Murtagh, "A Survey Of Recent Advances in Hierarchical Clustering Algorithms," *The Computer Journal*, vol. 26, no. 4, pp. 354-359, 1983.
- [37] A. Ozgur, "Supervised and Unsupervised Machine Learning Techniques for Text Document Categorization," *Unpublished Master's Thesis, İstanbul: Boğaziçi University*, 2004.
- [38] A. Kassambara, "Practical Guide to Cluster Analysis in R: Unsupervised Machine Learning," *Sthda*, vol. 1, 2017.
- [39] J. MacQueen, "Some Methods for Classification and Analysis of Multivariate Observations," *In Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*, vol. 1, no. 14, pp. 281-297, 1967.
- [40] J. Steuer, "Defining Virtual Reality: Dimensions Determining Telepresence," *Journal of Communication*, vol. 42, no. 4, pp. 73-93, 1992.
- [41] M. W. Kreuger, *Artificial Reality (2nd Ed)*, Reading, MA: Addison-Wesley, 1991.
- [42] L. Chan, M. E. Sandel, A. M. Jette, J. Appelman, D. E. Brandt, P. Cheng, M. TeSelle, R. Delmonico, J. F. Terdiman and E. K. Rasch, "Does Postacute Care Site Matter? A Longitudinal Study Assessing Functional Recovery After a Stroke," *Archives of Physical Medicine and Rehabilitation*, vol. 94, no. 4, pp. 622-629, 2013.
- [43] B. Cieślik, J. Mazurek, S. Rutkowski, P. Kiper, A. Turolla and J. Szczepańska-Gieracha, "Virtual Reality in Psychiatric Disorders: A Systematic Review of Reviews," *Complementary Therapies in Medicine*, vol. 102480, 2020.
- [44] D. Freeman, S. Reeve, A. Robinson, A. Ehlers, D. Clark, B. Spanlang and M. Slater, "Virtual Reality in the Assessment, Understanding, and Treatment of Mental Health Disorders," *Psychological Medicine*, vol. 47, no. 14, pp. 2393-2400, 2017.
- [45] K. Thielbar, N. Spencer, D. Tsoupikova, M. Ghassemi and D. Kamper, "Utilizing Multi-User Virtual Reality to Bring Clinical Therapy Into Stroke Survivors' Homes," *Journal of Hand Therapy*, 2020.

- [46] V. S. Pantelidis, "Virtual Reality in the Classroom," *Educational Technology*, no. 33A, pp. 23-27, 1993.
- [47] T. L. Jeffs, "Virtual Reality and Special Needs," *Themes in Science and Technology Education*, pp. 253-268, 2010.
- [48] W. Keay-Bright and I. Howarth, "Is Simplicity the Key to Engagement For Children on the Autism Apectrum?," *Personal and Ubiquitous Computing*, vol. 16, no. 2, p. 129–141, 2012.
- [49] H. Rosqvist, C. Brownlow and L. O'Dell, "Mapping the Social Geographies of Autism – Online and Off-Line Narratives of Neuro-Shared and Separate Spaces," *Disability & Society*, vol. 28, no. 3, p. 367–379, 2013.
- [50] M. Burke, R. Kraut and D. Williams, "Social Use of Computer-Mediated Communication By Adults on the Autism Spectrum," *Proceedings of the 2010 ACM Conference on Computer Supported Cooperative Work*, p. 425–434, 2010.
- [51] A. Hurst and J. Tobias, "Empowering Individuals With Do-It-Yourself Assistive Technology," in *13th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '11)*, New York(NY), 2011.
- [52] M. M. Sweitzer, K. K. Watson, S. R. Erwin, A. A. Winecoff, N. Datta, S. Huettel, M. L. Platt and N. L. Zucker, "Neurobiology of Social Reward Valuation in Adults With a History of Anorexia Nervosa," *PloS one*, vol. 13, no. 12, 2018.
- [53] K. R. Merikangas, J. P. He, M. Burstein, S. A. Swanson, S. Avenevoli, L. Cui, C. Benjet, K. Georgiades and J. Swendsen, "Lifetime Prevalence of Mental Disorders in US Adolescents: Results From the National Comorbidity Survey Replication–Adolescent Supplement (NCS-A)," *Journal of the American Academy of Child & Adolescent Psychiatry*, vol. 49, no. 10, p. 980–989, 2010.
- [54] J. I. Hudson, E. Hiripi, H. G. Pope Jr and R. C. Kessler, "The Prevalence and Correlates of Eating Disorders in the National Comorbidity Survey Replication," *Biological Psychiatry*, vol. 61, no. 3, p. 348–358, 2007.
- [55] J. Polivy and C. P. Herman, "Causes of Eating Disorders," *Annual Review of Psychology*, vol. 53, no. 1, p. 187–213, 2002.
- [56] L. Anderson, J. M. Shaw and L. McCargar, "Physiological Effects of Bulimia Nervosa on the Gastrointestinal Tract," *Canadian Journal of Gastroenterology and Hepatology*, vol. 11, no. 5, p. 451–459, 1997.
- [57] S. Nolen-Hoeksema, *Abnormal Psychology*, New York, NY: McGraw-Hill, 2011.

- [58] J. H. Crowther, M. Arney, K. H. Luce, G. R. Dalton and T. Leahey, "The Point Prevalence of Bulimic Disorders From 1990 to 2004," *International Journal of Eating Disorders*, vol. 41, no. 6, p. 491–497, 2008.
- [59] P. K. Keel, T. F. Heatherton, D. J. Dorer, T. E. Joiner and A. K. Zalta, "Point Prevalence of Bulimia Nervosa in 1982, 1992, and 2002," *Psychological Medicine*, vol. 36, no. 1, p. 119–127, 2006.
- [60] R. H. Striegel-Moore and C. M. Bulik, "Risk Factors for Eating Disorders," *American Psychologist*, vol. 62, no. 3, p. 181, 2007.
- [61] J. P. O'Doherty, "Reward Representations and Reward-Related Learning in the Human Brain: Insights From Neuroimaging," *Current Opinion in Neurobiology*, vol. 14, no. 6, p. 769–776, 2004.
- [62] E. Attia and B. T. Walsh, "Anorexia Nervosa," *American Journal of Psychiatry*, vol. 164, no. 12, pp. 1805-1810, 2007.
- [63] F. Brambilla, L. Bellodi, C. Arancio, P. Ronchi and D. Limonta, "Central Dopaminergic Function in Anorexia and Bulimia Nervosa A Psychoneuroendocrine Approach," *Psychoneuroendocrinology*, vol. 26, no. 4, p. 393–409, 2001.
- [64] G. K. Frank, W. H. Kaye, T. E. Weltzin, J. Perel, H. Moss, C. McConaha and C. Pollice, "Altered Response to Meta-Chlorophenylpiperazine in Anorexia Nervosa: Support for a Persistent Alteration of Serotonin Activity After Short-Term Weight Restoration," *International Journal of Eating Disorders*, vol. 30, no. 1, pp. 57-68, 2001.
- [65] G. K. Frank, U. F. Bailer, S. E. Henry, W. Drevets, C. C. Meltzer, J. C. Price, C. A. Mathis, A. Wagner, J. Hoge and S. Ziolko, "Increased Dopamine D2/D3 Receptor Binding After Recovery From Anorexia Nervosa Measured By Positron Emission Tomography and [11c] Raclopride," *Biological Psychiatry*, vol. 58, no. 11, pp. 908-912, 2005.
- [66] A. Broft, M. Slifstein, J. Osborne, P. Kothari, S. Morim, R. Shingleton, L. Kenney, S. Vallabhajosula, E. Attia, D. Martinez et al., "Striatal Dopamine Type 2 Receptor Availability in Anorexia Nervosa," *Psychiatry Research: Neuroimaging*, vol. 233, no. 3, 2015.
- [67] D. M. Garner and P. E. Garfinkel, "Socio-Cultural Factors in the Development of Anorexia Nervosa," *Psychological Medicine*, vol. 10, no. 4, pp. 647-656, 1980.
- [68] M. McCarthy, "The Thin Ideal, Depression and Eating Disorders in Women," *Behaviour Research and Therapy*, vol. 28, no. 3, p. 205–214, 1990.

- [69] J. Sobal and A. J. Stunkard, "Socioeconomic Status and Obesity: A Review of the Literature," *Psychological Bulletin*, 1989.
- [70] C. V. Wiseman, J. J. Gray, J. E. Mosimann and A. H. Ahrens, "Cultural Expectations of Thinness in Women: An Update," *International Journal of Eating Disorders*, vol. 11, no. 1, p. 85–89, 1992.
- [71] J. Sundgot-Borgen, "Risk and trigger factors for the development of eating disorders in female elite athletes," *Medicine & Science in Sports & Exercise*, 1994.
- [72] C. G. Fairburn, P. A. Norman, S. L. Welch, M. E. O'Connor, H. A. Doll and R. C. Peveler, "A Prospective Study of Outcome in Bulimia Nervosa and the Long-Term Effects of Three Psychological Treatments," *Archives of General Psychiatry*, vol. 52, no. 4, p. 304–312, 1995.
- [73] E. Stice, "Risk and maintenance factors for eating pathology: a meta-analytic review.," *Psychological bulletin*, vol. 128, no. 5, p. 825, 2002.
- [74] D. M. Clark, C. G. Fairburn, J. V. Jones et al., *The Science and Practice of Cognitive Behaviour Therapy*, Springer, 1997.
- [75] R. H. Striegel-Moore, L. R. Silberstein and J. Rodin, "The Social Self in Bulimia Nervosa: Public Self-Consciousness, Social Anxiety, and Perceived Fraudulence," *Journal of Abnormal Psychology*, vol. 102, no. 2, p. 297, 1993.
- [76] T. D. Wade, M. Tiggemann, C. M. Bulik, C. G. Fairburn, N. R. Wray and N. G. Martin, "Shared Temperament Risk Factors for Anorexia Nervosa: A Twin Study," *Psychosomatic Medicine*, vol. 70, no. 2, p. 239–244, 2008.
- [77] E. Stice and H. E. Shaw, "Adverse Effects of the Media Portrayed Thin-Ideal on Women and Linkages to Bulimic Symptomatology," *Journal of Social and Clinical Psychology*, vol. 13, no. 3, p. 288–308, 1994.
- [78] S. E. Mazzeo, S. E. Trace, K. S. Mitchell and R. W. Gow, "Effects of a Reality TV Cosmetic Surgery Makeover Program on Eating Disordered Attitudes and Behaviors," *Eating Behaviors*, vol. 8, no. 3, p. 390–397, 2007.
- [79] E. Stice, J. Maxfield and T. Wells, "Adverse Effects of Social Pressure to Be Thin on Young Women: An Experimental Investigation of the Effects of 'Fat Talk'," *International Journal of Eating Disorders*, vol. 34, no. 1, p. 108–117, 2003.
- [80] G. T. Wilson, *Assessment of Binge Eating*, Guilford Press, 1993.

- [81] K. H. Luce and J. H. Crowther, "The Reliability of the Eating Disorder Examination—Self-Report Questionnaire Version (EDE-Q)," *International Journal of Eating Disorders*, vol. 25, no. 3, p. 349–351, 1999.
- [82] F. Túry, H. Güleç and E. Kohls, "Assessment Methods for Eating Disorders and Body Image Disorders," *Journal of Psychosomatic Research*, vol. 69, no. 6, p. 601–611, 2010.
- [83] W. Vandereycken, "Denial of Illness in Anorexia Nervosa—A Conceptual Review: Part 1 Diagnostic Significance and Assessment," *European Eating Disorders Review: The Professional Journal of the Eating Disorders Association*, vol. 14, no. 5, p. 341–351, 2006.
- [84] D. A. Williamson, D. A. Anderson, L. P. Jackman and S. R. Jackson, *Assessment of Eating Disordered Thoughts, Feelings, and Behaviors*, Sage Publications, Inc, 1995.
- [85] T. D. Wade, S. Byrne and R. Bryant-Waugh, "The Eating Disorder Examination: Norms and Construct Validity With Young and Middle Adolescent Girls," *International Journal of Eating Disorders*, vol. 41, no. 6, p. 551–558, 2008.
- [86] L. B. Mintz, M. S. O'Halloran, A. M. Mulholland and P. A. Schneider, "Questionnaire for Eating Disorder Diagnoses: Reliability and Validity of Operationalizing DSM-IV Criteria Into a Self-Report Format," *Journal of Counseling Psychology*, vol. 44, no. 1, p. 63, 1997.
- [87] M. H. Thelen, J. Farmer, S. Wonderlich and M. Smith, "A Revision of the Bulimia Test: The BULIT-R," *Psychological Assessment: A Journal of Consulting and Clinical Psychology*, vol. 3, no. 1, p. 119, 1991.
- [88] M. H. Thelen, L. B. Mintz and J. S. Vander Wal, "The Bulimia Test-Revised: Validation with DSM-IV Criteria for Bulimia Nervosa," *Psychological Assessment*, vol. 8, no. 2, p. 219, 1996.
- [89] G. Welch, L. Thompson and A. Hall, "The BULIT-R: Its Reliability and Clinical Validity as a Screening Tool for DSM-III-R Bulimia Nervosa in a Female Tertiary Education Population," *International Journal of Eating Disorders*, vol. 14, no. 1, p. 95–105, 1993.
- [90] J. F. Morgan, F. Reid and J. H. Lacey, "The SCOFF Questionnaire: Assessment of a New Screening Tool for Eating Disorders," *BMJ*, vol. 319, no. 7223, p. 1467–1468, 1999.
- [91] D. M. Garner and P. E. Garfinkel, "The Eating Attitudes Test: An Index of the Symptoms of Anorexia Nervosa," *Psychological Medicine*, vol. 9, no. 2, p. 273–279, 1979.
- [92] K. Bohn and C. G. Fairburn, "The Clinical Impairment Assessment Questionnaire (CIA)," *Cognitive Behavioral Therapy for Eating Disorders*, p. 315–317, 2008.

- [93] P. J. Cooper, M. J. Taylor, Z. Cooper and C. G. Fairburn, "The Development and Validation of the Body Shape Questionnaire," *International Journal of Eating Disorders*, vol. 6, no. 4, p. 485–494, 1987.
- [94] M. Probst, W. Vandereycken, H. V. Coppenolle and J. Vanderlinden, "The Body Attitude Test for Patients with an Eating Disorder: Psychometric Characteristics of a New Questionnaire," *Eating Disorders*, vol. 3, no. 2, p. 133–144, 1995.
- [95] C. B. Peterson, R. D. Crosby, S. A. Wonderlich, T. Joiner, S. J. Crow, J. E. Mitchell, A. M. Bardone-Cone, M. Klein and D. Le Grange, "Psychometric Properties of the Eating Disorder Examination-Questionnaire: Factor Structure and Internal Consistency," *International Journal of Eating Disorders*, vol. 40, no. 4, p. 386–389, 2007.
- [96] J. K. Thompson, P. Van Den Berg, M. Roehrig, A. S. Guarda and L. J. Heinberg, "The Sociocultural Attitudes Towards Appearance Scale-3 (SATAQ-3): Development and Validation," *International Journal of Eating Disorders*, vol. 35, no. 3, p. 293–304, 2004.
- [97] S. G. Engel, D. A. Wittrock, R. D. Crosby, S. A. Wonderlich, J. E. Mitchell and R. L. Kolotkin, "Development and Psychometric Validation of an Eating Disorder-Specific Health-Related Quality of Life Instrument," *International Journal of Eating Disorders*, vol. 39, no. 1, p. 62–71, 2006.
- [98] C. E. Adair, G. C. Marcoux, B. S. Cram, C. J. Ewashen, J. Chafe, S. E. Cassin, J. Pinzon, J. L. Gusella, J. Geller, Y. Scattolon et al., "Development and Multi-Site Validation of a New Condition-Specific Quality of Life Measure for Eating Disorders," *Health and Quality of Life Outcomes*, vol. 5, no. 1, p. 23, 2007.
- [99] C. G. Fairburn, Z. Cooper, H. A. Doll, P. Norman and M. O'Connor, "The Natural Course of Bulimia Nervosa and Binge Eating Disorder in Young Women," *Archives of General Psychiatry*, vol. 57, no. 7, p. 659–665, 2000.
- [100] P. K. Keel, J. E. Mitchell, K. B. Miller, T. L. Davis and S. J. Crow, "Long-Term Outcome of Bulimia Nervosa," *Archives of General Psychiatry*, vol. 56, no. 1, p. 63–69, 1999.
- [101] M. Anderluh, K. Tchanturia, S. Rabe-Hesketh, D. Collier and J. Treasure, "Lifetime Course of Eating Disorders: Design and Validity Testing of a New Strategy to Define the Eating Disorders Phenotype," *Psychological Medicine*, vol. 39, no. 1, p. 105–114, 2009.
- [102] N. Grira, M. Crucianu and N. Boujemaa, "Unsupervised and Semi-Supervised Clustering: A Brief Survey," *A Review of Machine Learning Techniques for Processing Multimedia Content*, vol. 1, pp. 9-16, 2004.
- [103] M. Usama, J. Qadir, A. Raza, H. Arif, K. L. A. Yau, Y. Elkhatib, A. Hussain and A. Al-Fuqaha, "Unsupervised Machine Learning for Networking: Techniques, Applications and Research Challenges," *IEEE Access*, vol. 7, p. 65579–65615, 2019.

- [104] A. McGregor, M. Hall, P. Lorier and J. Brunskill, "Flow Clustering Using Machine Learning Techniques," *International Workshop on Passive and Active Network Measurement*, p. 205–214, 2004.
- [105] R. Xu and D. Wunsch, "Survey of Clustering Algorithms," *IEEE Transactions on Neural Networks*, vol. 16, no. 3, p. 645–678, 2005.
- [106] X. Zhu and A. B. Goldberg, "Introduction to Semi-Supervised Learning," *Synthesis Lectures on Artificial Intelligence and Machine Learning*, vol. 3, no. 1, p. 1–130, 2009.
- [107] M. M. Fichter, M. Elton, K. Engel, A. E. Meyer, H. Mall and F. Poustka, "Structured Interview for Anorexia and Bulimia Nervosa (SIAB): Development of a New Instrument for the Assessment of Eating Disorders," *International Journal of Eating Disorders*, vol. 10, no. 5, p. 571–592, 1991.
- [108] C. G. Fairburn, *Cognitive Behavior Therapy and Eating Disorders*, Guilford Press, 2008.
- [109] C. L. Dahlgren, K. Stedal and Ø. Rø, "Eating Disorder Examination Questionnaire (EDE-Q) and Clinical Impairment Assessment (CIA): Clinical Norms and Functional Impairment in Male and Female Adults with eating Disorders," *Nordic Journal of Psychiatry*, vol. 71, no. 4, p. 256–261, 2017.
- [110] E. Welch, A. Birgegård, T. Parling and A. Ghaderi, "Eating Disorder Examination Questionnaire and Clinical Impairment Assessment Questionnaire: General Population and Clinical Norms for Young Adult Women in Sweden," *Behaviour Research and Therapy*, vol. 49, no. 2, pp. 85-91, 2011.
- [111] C. G. Fairburn and S. J. Beglin, "Assessment of Eating Disorders: Interview or Self-Report Questionnaire?," *International Journal of Eating Disorders*, vol. 16, no. 4, p. 363–370, 1994.
- [112] J. Mond, P. Hay, B. Rodgers, C. Owen and P. Beumont, "Validity of the Eating Disorder Examination Questionnaire (EDE-Q) in Screening for Eating Disorders in Community Samples," *Behaviour Research and Therapy*, vol. 42, no. 5, p. 551 – 567, 2004.
- [113] K. Bohn, H. A. Doll, Z. Cooper, M. O'Connor, R. L. Palmer and C. G. Fairburn, "The Measurement of Impairment Due to Eating Disorder Psychopathology," *Behaviour Research and Therapy*, vol. 46, no. 10, p. 1105–1110, 2008.
- [114] S. Baron-Cohen, S. Wheelwright, R. Skinner, J. Martin and E. Clubley, "The Autism-Spectrum Quotient (AQ): Evidence From Asperger Syndrome/High-Functioning Autism, Males and Females, Scientists and Mathematicians," *Journal of Autism and Development*, vol. 31, no. 1, p. 5–17, 2001.

- [115] S. Baron-Cohen, R. A. Hoekstra, R. Knickmeyer and S. Wheelwright, "The Autism-Spectrum Quotient(AQ)—Adolescent Version," *Journal of Autism and Developmental Disorders*, vol. 36, no. 3, p. 343, 2006.
- [116] P. Rousseeuw, "Silhouettes: A Graphical Aid to the Interpretation and Validation of Cluster Analysis," *Journal of Computational and Applied Mathematics*, vol. 20, no. 1, pp. 53-65, 1987.
- [117] J. Baarsch and M. E. Celebi, "Investigation of Internal Validity Measures For K-Means Clustering," *Proceedings of the International Multiconference of Engineers and Computer Scientists*, vol. 1, p. 14–16, 2012.
- [118] E. Kocabey, F. Ofli, J. Marin, A. Torralba and I. Weber, "Using Computer Vision to Study the Effects of BMI on Online Popularity and Weight-Based Homophily," *International Conference on Social Informatics*, pp. 129-138, 2108.
- [119] L. Wen and G. Guo, "A Computational Approach to Body Mass Index Prediction From Face Images," *Image and Vision Computing*, vol. 31, no. 5, pp. 392-400, 2013.
- [120] I. Weber and Y. Mejova, "Crowdsourcing Health Labels: Inferring Body Weight From Profile Pictures," *In Proceedings of the 6th International Conference on Digital Health Conference*, pp. 105-109, 2016.
- [121] A. Pantanowitz, E. Cohen, P. Gradidge, N. Crowther, V. Aharonson, B. Rosman and D. M. Rubin, "Estimation of Body Mass Index From Photographs Using Deep Convolutional Neural Networks," *arXiv preprint arXiv:1908.11694*, 2019.
- [122] N. Ahad, J. Qadir and N. Ahsan, "Neural Networks in Wireless Networks: Techniques, Applications and Guidelines," *Journal of Network and Computer Applications*, vol. 68, pp. 1-27, 2016.
- [123] S. Lloyd, "Least Squares Quantization in PCM," *IEEE Transactions on Information Theory*, vol. 28, no. 2, pp. 129-137, 1982.
- [124] H. F. Köhn and L. J. Hubert, "Hierarchical cluster analysis," *Wiley StatsRef: statistics reference online*, pp. 1-13, 2014.
- [125] Z. Zhang, F. Murtagh, S. Van Poucke, S. Lin and P. Lan, "Hierarchical Cluster Analysis in Clinical Research With Heterogeneous Study Population: Highlighting Its Visualization With R," *Annals of Translational Medicine*, vol. 5, no. 4, 2017.
- [126] D. A. Frederick, G. B. Forbes, K. Grigorian and J. M. Jarcho, "The UCLA Body Project I: Gender and Ethnic Differences in Self-Objectification and Body Satisfaction Among 2,206 Undergraduates," *Sex Roles*, vol. 57, pp. 317-327, 2007.

- [127] D. A. Frederick, G. Sandhu, P. J. Morse and V. Swami, "Correlates of Appearance and Weight Satisfaction in a U.S. National Sample: Personality, Attachment Style, Television Viewing, Self-Esteem, and Life Satisfaction," *Body Image*, vol. 17, pp. 191-203, 2016.
- [128] J. Baio, L. Wiggins, D. L. Christensen, M. J. Maenner, J. Daniels, Z. Warren, M. Kurzius-Spencer et al., "Prevalence of Autism Spectrum Disorder Among Children Aged 8 Years—Autism and Developmental Disabilities Monitoring Network, 11 Sites, United States, 2014," *MMWR Surveillance Summaries*, vol. 67, no. 6, p. 1–23, 2018.
- [129] C. J. Park, G. W. Yelland, J. R. Taffe and K. M. Gray, "Brief Report: The Relationship Between Language Skills, Adaptive Behavior, and Emotional and Behavior Problems in Pre-Schoolers with Autism," *Journal of Autism and Developmental Disorders*, vol. 42, no. 12, p. 2761–2766, 2012.
- [130] S. Herring, K. Gray, J. Taffe, B. Tonge, D. Sweeney and S. Einfeld, "Behaviour and Emotional Problems in Toddlers with Pervasive Developmental Disorders and Developmental Delay: Associations with Parental Mental Health and Family Functioning," *Journal of Intellectual Disability Research*, vol. 50, no. 12, p. 874–882, 2006.
- [131] M. H. Charlop-Christy, M. Carpenter, L. Le, L. A. LeBlanc and K. Kellet, "Using the Picture Exchange Communication System (PECS) with Children with Autism: Assessment of PECS Acquisition, Speech, Social-Communicative Behavior, and Problem Behavior," *Journal of Applied Behavior Analysis*, vol. 35, no. 3, p. 213–231, 2002.
- [132] R. M. Reese, D. M. Richman, J. M. Belmont and P. Morse, "Functional Characteristics of Disruptive Behavior in Developmentally Disabled Children With and Without Autism," *J. Autism Dev. Disord.*, vol. 35, no. 4, p. 419–428, 2005.
- [133] T. A. Lavelle, M. C. Weinstein, J. P. Newhouse, K. Munir, K. A. Kuhlthau and L. A. Prosser, "Economic Burden of Childhood Autism Spectrum Disorders," *Pediatrics*, vol. 133, p. e520–e529, 2014.
- [134] T. T. Shimabukuro, S. D. Grosse and C. Rice, "Medical Expenditures for Children with an Autism Spectrum disorder in a Privately Insured Population," *Journal of Autism and Developmental Disorders*, vol. 38, no. 3, p. 546–552, 2008.
- [135] A. Alcorn, H. Pain, G. Rajendran, T. Smith, O. Lemon, K. Porayska-Pomsta, M. E. Foster, K. Avramides, C. Frauenberger and S. Bernardini, "Social Communication Between Virtual Characters and Children with Autism," in *International Conference on Artificial Intelligence in Education, Auckland, New Zealand*, Berlin/Heidelberg, Germany, 2011.
- [136] D. Moore, Y. Cheng, P. McGrath and N. J. Powell, "Collaborative Virtual Environment Technology for People with Autism," *Focus on Autism and Other Developmental Disabilities*, vol. 20, no. 4, p. 231–243, 2005.

- [137] A. Tartaro and J. Cassell, "Authorable Virtual Peers for Autism Spectrum Disorders," in *The Combined Workshop on Language-Enabled Educational Technology and Development and Evaluation for Robust Spoken Dialogue Systems at the 17th European Conference on Artificial Intelligence*, Riva del Garda, Italy, 2006.
- [138] S. Parsons, A. Leonard and P. Mitchell, "Virtual Environments for Social Skills Training: Comments From Two Adolescents with Autistic Spectrum Disorder," *Computers and Education*, vol. 47, no. 2, p. 186–206, 2006.
- [139] M. E. Hoque, M. Courgeon, J. C. Martin, B. Mutlu and R. W. Picard, "Mach: My Automated Conversation Coach," in *The 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing, Zurich, Switzerland*, New York, NY, 2013.
- [140] American Psychiatric Association, *Neurodevelopmental Disorders: DSM-5® Selections*, Washington, DC: American Psychiatric Pub, 2015.
- [141] C. E. Robertson and S. Baron-Cohen, "Sensory Perception in Autism," *Nature Reviews Neuroscience*, vol. 18, no. 11, p. 671, 2017.
- [142] U. Will, "Temporal Processing and the Experience of Rhythm: A Neuro-Psychological Approach," in *The Nature of Rhythm: Aesthetics, Music, Dance and Poetics*, 2017.
- [143] M. Grandgeorge, S. Tordjman, A. Lazartigues, E. Lemonnier, M. Deleau and M. Hausberger, "Does Pet Arrival Trigger Prosocial Behaviors in Individuals with Autism?," *PLoS ONE*, vol. 7, no. 8, p. e41739, 2012.
- [144] G. K. Carlisle, "The Social Skills and Attachment to Dogs of Children with Autism Spectrum Disorder," *Journal of Autism and Developmental Disorders*, vol. 45, no. 5, p. 1137–1145, 2015.
- [145] M. South, S. Ozonoff and W. M. McMahon, "Repetitive Behavior Profile in Asperger Syndrome and High-Functioning Autism," *Journal of Autism and Developmental Disorders*, vol. 35, no. 2, p. 145–158, 2005.
- [146] R. J. Gaylord-Ross, T. G. Haring, C. Breen and V. Pitts-Conway, "The Training and Generalization of Social Interaction Skills with Autistic Youth," *Journal of Applied Behavior Analysis*, vol. 17, no. 2, p. 229–247, 1984.
- [147] B. R. Ferguson, J. M. Gillis and M. Sevlever, "A Brief Group Intervention Using Video Games to Teach Sportsmanship Skills to Children with Autism Spectrum Disorders," *Child and Family Behavior Therapy*, vol. 35, no. 4, p. 293–306, 2013.

- [148] B. S. Myles, M. Trautman and R. L. Schelvan, *The Hidden Curriculum: Practical Solutions for Understanding Unstated Rules in Social Situations*, Shawnee Mission (KS): Autism Asperger Pub. Co, 20014.
- [149] P. A. Sánchez, F. S. Vázquez and L. A. Serrano, "Autism and the Built Environment," *Autism Spectrum Disorders-From Genes to Environment*, vol. 19, pp. 363-380, 2011.
- [150] H. Hutchinson, W. Mackay, B. Westerlund, B. B. Bederson, A. Druin, C. Plaisant, M. Beaudouin-Lafon, S. Conversy, H. Evans, H. Hansen et al., "Technology Probes: Inspiring Design for and with Families," in *The SIGCHI Conference on Human Factors in Computing Systems, CHI '03, Ft. Lauderdale, FL, USA*, New York, NY, 2003.
- [151] J. M. Corbin and A. Strauss, *Basics of Qualitative Research; Techniques and Procedures for Developing Grounded Theory*, 3rd Ed., Thousand Oaks, CA: Sage Publications, 2008.
- [152] R. Bradley and N. Newbutt, "Autism and Virtual Reality Head-Mounted Displays: A State of the Art Aystematic Review," *Journal of Enabling Technologies*, vol. 12, no. 3, p. 101–113, 2018.
- [153] N. Newbutt, C. Sung, H. J. Kuo, M. J. Leahy, C. C. Lin and B. Tong, "Brief Report: A Pilot Study of the Use of a Virtual Reality Headset in Autism Populations," *Journal of Autism and Developmental Disorders*, vol. 46, no. 9, p. 3166–3176, 2016.
- [154] O. Bogdashina, *Sensory Perceptual Issues in Autism and Asperger Syndrome: Different Sensory Experiences - Different Perceptual Worlds*, 2nd Ed., United Kingdom: Jessica Kingsley Publishers, 2016.
- [155] S. V. Cobb, "Virtual Environments Supporting Learning and Communication in Special Needs Education," *Topics in Language Disorders*, vol. 27, no. 3, p. 211–225, 2007.
- [156] A. Rutten, S. Cobb, H. Neale, S. Kerr, A. Leonard, S. Parsons and P. Mitchell, "The AS Interactive Project: Single-User and Collaborative Virtual Environments for People with High-Functioning Autistic Spectrum Disorders," *The Journal of Visualization and Computer Animation*, vol. 14, no. 5, p. 233–241, 2003.