Evaluation of a Biofeedback Intervention in College Students Diagnosed with Autism

Spectrum Disorders

by

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ABSTRACT

This study used exploratory data analysis (EDA) to examine the use of a biofeedback intervention in the treatment of anxiety for college students diagnosed with an Autism Spectrum Disorder (ASD) (n=10) and in a typical college population (n=37). The use of EDA allowed for trends to emerge from the data and provided a foundation for future research in the areas of biofeedback and accommodations for college students with ASD. Comparing the first five weeks of the study with the second five weeks of the 10 week study, both groups showed improvement in their control of heart rate variability, a physiological marker for anxiety used in biofeedback. The ASD group showed greater gains, more consistent gains, and less variability in raw scores than the typical group. EDA also revealed a pattern between participant attrition and a participant's biofeedback progress. Implications are discussed.

DEDICATION

This work is dedicated to the outstanding teachers, mentors, friends, and family who have provided inspiration, motivation, and endless compassion in support of education.

ACKNOWLEDGMENTS

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Chapter 1

INTRODUCTION TO THE STUDY

Background

The most recent estimates from the Centers for Disease Control and Prevention [CDC] (2013) are that 1 in 50 children in the United States are diagnosed with an Autism Spectrum Disorder (ASD). Children and young adults with ASD are the sixth largest disability group in k-12 education (Chiang, Cheung, Hickson, Xiang, & Tsai, 2012). Unfortunately, and reinforced by this most recent CDC report, the literature continues to largely focus on children with ASD – ignoring that children with ASD grow into young adults with unique needs. For example, 43% of young adults with ASD enroll in colleges or universities post-high school; however, due to a lack of literature and research-based best practice, institutions of higher education are unprepared to accommodate the rising number and unique needs of students with ASD, resulting in poor quality of life, low graduation rates, and diminished employment outcomes (Camarena & Sarigiani, 2009; Chiang et al., 2012; Glennon, 2001; VanBergeijk, Klin, & Volkmar, 2008).

Compounding the challenges facing unprepared colleges and universities are that students with ASD are at an increased risk for co-morbid conditions such as anxiety, and due to poor insight and awareness, often refuse or do not seek help and assistance (Adreon & Durocher, 2007, Glennon, 2001; Hughes, 2009; VanBergeijk et al., 2008). McCoy (2012) found that mental health issues such as anxiety and depression are on the rise and impact 40-45% of children and adolescents with ASD. Traditional talk therapy approaches are often ineffective or insufficient due to the inherent social deficits present in individuals with ASD (Ramsay, Brodkin, Cohen, Listerud, Rostain, & Ekman, 2005).

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In response to these challenges, colleges and universities must be proactive in identifying new and innovative solutions for students with ASD that are affordable, sustainable, and effective.

Disability professionals working in college and university Disability Resource Centers (DRC) are the frontline service providers to students with ASD, and as a result, have unique insight into the needs of this population. This study investigates the introduction of a biofeedback software program by a public university DRC in response to the needs of students with ASD.

Biofeedback is a promising tool, and implemented by the DRC in this study, because biofeedback uses physiological markers such as heart rate variability (HRV) to inform users and professionals about levels of well-being such as anxiety. Because biofeedback is a new technology, particularly for use in college students with ASD, the analysis of data in this study is of critical importance in shaping future work in this field.

Published research typically relies on traditional techniques such as confirmatory data analysis (CDA) in the reporting of study results. In well documented fields of study, with large volumes of pre-existing literature, the development and testing of specific hypotheses is justified, because new hypotheses are based on established trends and patterns that emerged from previous research. The challenge facing research in new fields of study, such as interventions in college students with ASD, is that without historical data and models any hypothesis generated by a researcher is ungrounded and likely to miss critical aspects of the novel population or approach being studied (Behrens, 1997; Cohen, 1994). Exploratory Data Analysis (EDA) is a powerful solution for the study of novel disciplines, because EDA applies highly visual computational tools - patterns,

trends, and discoveries emerge and can lead to the development of models or well reasoned hypotheses for future research.

This study documents the use of an EDA based approach to data analysis by identifying patterns and trends in program data related to the impact of biofeedback on the anxiety level of individuals with autism. Information learned from this study will contribute to the literature related to the utility of EDA as well as a beginning point for identification of patterns or trends in data related to biofeedback and autism in young adults.

Conceptual Underpinnings

Although data on graduation and retention rates for students with ASD is unavailable, students with disabilities in postsecondary education typically experience a 53% completion rate compared to 64% for students without disabilities (U.S. Department of Education, 1999). Investigation is sorely needed into the experiences and outcomes of students with ASD in postsecondary education, particularly as they are the largest and fastest growing special education population in America (Chiang et al., 2012; VanBergeijk et al., 2008).

Multiple factors are responsible for the sudden rise in transition to postsecondary education for young adults with ASD. VanBergeijk et al., (2008) cites the surge of ASD diagnoses in the 1990's leading to a wave of young adults with ASD who are now reaching college age. This wave of young adults with ASD benefited from strategies and early interventions that make them more academically qualified for postsecondary education than at any time in the past (Dillon, 2007; VanBergeijk et al., 2008). Camarena and Sarigiani (2009) offer evidence that parents may be influencing the rise in college

attendance by encouraging and expecting young adults with ASD to transition to higher education post high school.

The United States Department of Education is also a factor in rising rates of college attendance for individuals with ASD. The Department of Education recently unveiled a five-year plan to offer transition programs at 27 colleges and universities for students with ASD and co-morbid intellectual disabilities (Nevill & White, 2011).

This new initiative by the Department of Education, in conjunction with already increasing rates and access to interventions, dramatically increases the pressure on institutions of higher education. Investigation must continue to uncover and explore best practices to assure the success of this growing population on college and university campuses.

The literature demonstrates that few colleges and universities are prepared to serve this growing population (Farrell, 2004; Glennon, 2001; Smith, 2007; VanBergeijk et al., 2008; Wolf, Brown, & Bork, 2009; Zager & Alpern, 2010). Additionally, a lack of literature exists regarding supports for college students with ASD, and this absence has serious consequences. Glennon (2001) and VanBergeijk et al. (2008) report that anxiety levels in college students with ASD rise to dangerous levels in response to the social and environmental demands of the college experience. Glennon (2001) argues that failure to address the mental health needs of college students with ASD puts them, "at increased risk for depression and perhaps increased risk of suicide" (p. 1366). Anxiety is one the chief contributing factors to the poor mental health of college students with ASD (Glennon, 2001; VanBergeijk et al., 2008; Wolf, 2009).

An emerging strategy for managing anxiety across populations is the use of

biofeedback, a system that monitors an individual's physical response to stress such as heart rate, heart rate variability (HRV), and other biometric data. Thompson, Thompson, and Reid (2010) report that HRV, one measure of biofeedback, is a strong marker for anxiety. HRV is easy to measure, and non-invasive, making the technique an ideal instrument for studies of anxiety. Biofeedback technology has evolved to not only be an effective intervention for anxiety, but cost effective, easy to use, and widely available. Colleges and universities are recognizing the opportunity that biofeedback offers as a campus resource and are adopting it in greater numbers (Ratanasiripong, Sverduk, Hayashino, Prince, 2010).

Summary

The past decade brought an increase in awareness and diagnosis of ASD in children, and has created a current surge in the number of young adults with ASD who are facing a critical transition to postsecondary settings. Almost half of all high school students with ASD are considering and attending colleges and universities; however, little literature exists on how to accommodate or meet the needs of these students in higher education. The transition to college life can tax the poor coping skills of students with ASD and exacerbate existing co-morbid conditions such as anxiety. The resulting impact on college students with ASD is increased anxiety, risk of academic failure, poor quality of life, and even self harm.

Disability service providers in higher education are forced to address these concerns and are adopting new strategies and techniques. Biofeedback is one technique with a history of successfully treating anxiety in adults with and without ASD. This study

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reports on the findings of one university DRC office that implemented a biofeedback program for their college students with ASD.

      A CDA approach to the data in this study would be inappropriate given the current lack of research on college students with ASD using biofeedback. Therefore, this study takes an EDA approach in order to provide the greatest benefit to the field, and contribute to a foundational level of understanding on the use of biofeedback in college students with ASD. This study's use of an EDA based analysis of the data provides disability service professionals, the field of ASD, the field of biofeedback, and the field of EDA with insight into the use of biofeedback in college students with ASD, and contributes to future academic research on the use of biofeedback and EDA as tools for intervention and evaluation.

Chapter 2

LITERATURE REVIEW

This study explores a biofeedback intervention in college students with ASD through the use of EDA. An interdisciplinary approach is utilized in the review of literature for this study. The five main areas addressed in this review of literature are: the accommodation experience of college students with ASD, the role of anxiety in quality of life, co-morbidity of anxiety and ASD, the emergence and effectiveness of biofeedback as an intervention for anxiety, and the use of EDA as a computational tool for program evaluation and as a catalyst for future research. Each of the five areas covered in this literature review provide insight into the current challenges facing college students with ASD. Collectively, these areas provide hope that new techniques and approaches may offer therapeutic interventions that benefit an emerging and underserved population, and that the appropriate use of analytical tools such as EDA offer incredible value to researchers in the identification of trends and the discovery of often overlooked aspects of data through more conventional CDA approaches.

Accommodations in Postsecondary Education

Colleges and universities that accept federal funding, like financial aid, are required to accommodate students with disabilities under section 504 of the Rehabilitation Act and the Americans with Disabilities Act (ADA) of 1990 – now the ADA Amendments Act (ADAAA) (Simon, 2011). Despite laws mandating access to higher education, students with disabilities, particularly those with ASD, are not offered the level of accommodation necessary for success (Hughes, 2009; VanBergeijk, 2008; Zager & Alpem, 2010). The future for students with ASD in higher education will remain

grim as long as services and accommodations fail to meet the minimum level of access as prescribed by federal law. Literature documents high anxiety, stress, and a poor quality of life for students with ASD in higher education who struggle without appropriate accommodations (Camarena & Sarigiani, 2009; Chiang et al., 2012; Glennon, 2001; Klin, & Volkmar, 2008; VanBergeijk, 2008; Wolf et al., 2009). Given the increasing numbers of young adults diagnosed with ASD, and the demand for postsecondary education in this population, evaluation and review of accommodations and services must occur to improve quality of life outcomes in this population (Dillon, 2007; Hughes, 2009; Smith, 2007).

Unlike students with learning disabilities who have been accommodated for decades, a lack of information and experience accommodating students with ASD exists in higher education and poses great risks for student success (Dillon, 2007; Hughes, 2009; Wenzel & Rowley, 2010; Wolf et al., 2009; Zager & Alpern, 2010). While the ADAAA and Section 504 provide for reasonable accommodations, the needs of students with ASD are different from the typical student with a learning disability and therefore these challenges must be explored to make progress. Future research must focus on the treatment of anxiety in college students with ASD in order to provide learning environments that are accessible, safe, and conducive to learning for this currently underserved population.

Anxiety and Quality of Life

The impact of anxiety on quality of life (QOL) for college students with ASD is a critical issue facing higher education. The Diagnostic and Statistical Manual of Mental Disorders, 4th Edition, Text Revision (DSM-IV-TR) lists nine types anxiety disorders

(American Psychiatric Association, 2000). According to a 2006 study by the American College Health Association 13% of college students suffer from anxiety in a 12 month period (American College Health Association, 2007). The presence of anxiety is concerning because it has an impact on aspects of daily living that makeup an individual's QOL (Mogotsi, Kaminer, & Stein, 2000). Poor life satisfaction, general well-being, social function, and perceived living conditions are all negatively impacted by the presence of anxiety (Mendlowicz & Stein, 2000; Mogotsi et al., 2000). The negative impact of anxiety disorders on QOL necessitates an effective intervention to reduce anxiety, which in turn will improve QOL.

  Impact of anxiety on QOL for college students with disabilities. The transition to college and time spent pursuing a degree can be stressful for all students, but for students with disabilities this period can bring an increase in anxiety greater than for the typical student (Davis III, Nida, Zlomke, & Nebel-Schwalm, 2008; Edwards, Patrick, & Topolski, 2003; Pancer, Hunsberger, Pratt, & Alisat, 2000). Reasons for this increase include poor coping skills for handling the transition from high school to college, adapting to greater independence as an adult, and the vastly different demands of college, academic and social, compared to high school (Pancer et al., 2000). For students with ASD, these factors often translate into greater anxiety and poorer QOL than other student populations because students with ASD display poor social and communication skills which in the highly social and communication rich environment of a college campus can be isolating and increase anxiety (Glennon, 2001; VanBergeijk et al., 2008).

  Edwards et al. (2003) examined the impact of anxiety reporting that, "Forty-six percent of adolescents with disabilities in this study reported missing out on activities

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they wanted to do fairly or very often versus 16% of those without disabilities" (p.238). This finding is supported by Davis III et al. (2008), who argued that, "for a proportion of students with learning disabilities accommodations may work, but academic success may be supplanted by other psychological variables" (p. 233). The trend in the literature suggests that stress and anxiety in college students with disabilities negatively impacts QOL due to lack of engagement in activities, environmental stressors, and preexisting mental health conditions.

Anxiety in College Students with ASD

The literature on anxiety in college students with ASD presents a disturbing picture compared with other disability subgroups such as those with learning disabilities. VanBergeijk et al. (2008) report that children diagnosed with an ASD in the 1990s are now facing transition to college or postsecondary settings (p. 1359). Few college faculty and staff are prepared to support this population of students (Wolf et al., 2009). The influx of students with ASD transitioning to college means that the unique needs of these students are not likely to be addressed, thus creating even greater potential for anxiety. Also of concern is that individuals with ASD are at greater risk for anxiety than the general population (Ghaziuddin, Ghaziuddin, & Greden, 2002; Kim, Szatmari, Bryson, Streiner, & Wilson, 2000; MacNeil, Lopes, & Minnes, 2009).

Anxiety in children or adolescents is a significant predicator for anxiety in adults (Pine, Cohen, Gurley, Brook, & Ma, 1998). Kim et al. (2000) studied a population with ASD and found that, "children with anxiety and mood problems were more aggressive, limited their parents' social activities and had poorer relationships with teachers, peers

and family members" (p. 127). The high incidence of children with ASD who struggle with anxiety will mature into young adults and adults with anxiety.

The negative influence of anxiety on QOL is clearly present in college and university setting for individuals with ASD. VanBergeijk et al. (2008) have described contributing factors influencing anxiety in college and university students

During the first semester the student's skills will be taxed. The novelty of the new environment will elevate the student's anxiety. This will be further exacerbated by the negotiations of a complex social environment in the dorms. The lack of familiar routine and structure will compound the student's anxiety (p. 1366).

Given the limited expertise among faculty and staff, increasing numbers of students with ASD entering college, and the high rates of anxiety continuing in this population an emphasis on effective, practical, and affordable interventions to improve outcomes must be developed.

Glennon (2001) argues that colleges must develop strategies so that the experience of students with ASD is free of fear, anxiety, and stress in order to achieve positive outcomes (p. 189). In order to achieve these outcomes, Glennon (2001) believes that new research on neurological functioning, academic interventions, and support strategies should be continually evaluated to limit fear, anxiety and stress in the experience of college students with ASD (p. 189). VanBergeijk et al. (2008) agrees, and sees a need for greater awareness of the issue facing this population. In addition, VanBergeijk et al. (2008) recommend that the mental health professionals serving this population be aware of co-morbid conditions, because, "without such proactive supports these students are at increased risk for depression and perhaps increased risk of suicide"

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(VanBergeijk et al., 2008, p. 1366). The pre-existing anxiety of students with ASD due to the high pressure to transition to new settings and social environment present in institutions of higher education places such students at ever greater risk. The very real danger of self harm associated with anxiety and poor QOL in college students with ASD has identified this population as one for which development, implementation and evaluation of strategic interventions is immediate.

ASD and cognitive behavioral therapy. Why individuals with ASD are at greater risk for developing mood disorders, such as anxiety, is not fully understood; however, standard treatments for mood disorders such as cognitive behavioral therapy (CBT) are growing in popularity (Attwood, 2003; Ghaziuddin, et al., 2002; Hare, 1997; Howlin, 2002; Kim, et al., 2000). CBT is a form of therapy that helps clients identify their reactions and responses to stimuli and retrain and reorient how they think, feel, and act in the moment (Attwood, 2003; Hare, 1997; Howlin, 2002). Attwood (2003) argued that with modifications CBT could be effective with individuals with ASD, but acknowledged that research in this area was limited and based largely on individual case-studies and that further research was needed.

Hare (1997) and Cardaciotto & Herbert (2004) both offer supporting evidence, via case-study examples, that CBT can be used in the treatment of anxiety in individuals with ASD. Although these findings offer some evidence that CBT may be a beneficial treatment for anxiety in individuals with ASD, CBT often requires ongoing therapy sessions with a licensed professional that can be time consuming and expensive. Observations from Hare (1997) were that the specific aspects of CBT that were

successful in working with this client were unknown, but that the use of visual feedback such as written instructions and information may have positively influenced the outcome.

Traditional talk therapy models such as CBT, dialectic behavior therapy, and humanistic therapies often rely on multiple visits with a highly trained and licensed mental health provider. Additionally, Ramsay et al. (2005) acknowledged that individuals with ASD may have a hard time establishing rapport with therapists because of the social challenges experienced by people with ASD. For college students making the difficult transition to a new environment, schedule, and campus lifestyle CBT and other talk therapies may prove too expensive, inaccessible on campus, or be to socially demanding to be successful. New approaches that provide real-time visual feedback, such as computer-based biofeedback software, offer a plausible alternative to traditional talk therapy.

Biofeedback as a Tool to Control Anxiety

One recent innovation in the treatment of anxiety disorders, and their significant impact on QOL, is biofeedback. Biofeedback based interventions are becoming increasingly popular in the treatment of anxiety and other mental health conditions (Coben, Linden, & Myers, 2009; Hammond, 2005; Reiner, 2008). Hammond (2005) argues that biofeedback has the ability to modify brain patterns that can reduce anxiety and depression. Biofeedback is non-invasive, in contrast to pharmaceuticals, shock therapy, and transcranial magnetic stimulation (Hammond, 2005, p. 135-136). Biofeedback is well suited for interventions to address anxiety because the autonomic nervous systems (ANS) is heavily engaged in the production of anxiety (Appelhans & Luecken, 2006, p. 229). Anxiety is identifiable by a physiological response, shortness of

breath for example, which makes using a physiological based intervention, such as biofeedback, a logical solution. The same systems that produce the physical feelings of anxiety can be retrained through biofeedback to reduce the body's physiological response to stress (McCraty, Atkinson, Tomasino, & Bradley, 2009; McCraty, Barrios-Choplin, Rozman, Atkinson, & Watkins, 1998).

Because the field of biofeedback originated using more complex and expensive equipment the majority of literature on biofeedback relies on these techniques; however, recent research in the field relies on less expensive and more robust technology (Coben et al., 2009; Hammond, 2005; Reiner, 2008). Advances in technology mean that newer biofeedback systems are less invasive and only require finger or earlobe contacts to record physiological data such as HRV. In contrast, older biofeedback methods such as electroencephalogram (EEG) and neurofeedback systems require multiple connection points, medical oversight, and record brainwave data in addition to physiological data such as HRV (Coben et al., 2009).

The chief benefit of biofeedback, early versions or recent advances, is the presentation of data, such as HRV, in an easy to interpret computer-based format. McCraty et al. (2009) discovered that the visual patterns of activation recorded by biofeedback were representative of emotional states such as anxiousness. A pattern identified by Friedman and Thayer (1997) was a strong connection between low HRV and the prevalence of anxiety disorders in adults (p. 141). This finding is significant because in addition to HRV being a predictor of future anxiety disorders, the HRV data available in real-time serves as marker to identify emotional states and track an individual's response to intervention (Appelhans & Luecken, 2006).

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Literature supports the use of HRV as a measure for anxiety and biofeedback as a technique for treatment of anxiety (Coben et al., 2009; Hammond, 2005; Reiner, 2008). In a study by Reiner (2008), a biofeedback intervention outperformed other established strategies for stress reduction, "73.3% (N = 11/15) reported finding the device more helpful and relaxing than unassisted breathing exercises, 77.8% (N = 7/9) more helpful than meditation, and 75% (N = 3/4) more helpful than yoga" (p. 58).

Another study examined the impact of HRV and a biofeedback intervention on test anxiety in high school students. Bradley, McCraty, Atkinson, Tomasino, Daugherty, and Arguelles (2010) found that high school students who received the biofeedback intervention displayed a pattern of improvement in HRV measures and were therefore better able to manage their emotions under stressful circumstances such as tests (p. 261). McCraty at al. (1998) argue that biofeedback interventions play an important role because they are fast acting, easy to implement, and low cost. The result of the intervention is that "individuals who learned to "reprogram" their conditioned emotional responses experienced significantly lower stress levels, less negative and more positive emotions" (McCraty et al., 1998, p. 167).

Biofeedback in individuals with ASD. Thompson, Thompson, and Reid (2010) studied the effect of neurofeedback and biofeedback training with 150 clients diagnosed with Asperger's Syndrome (AS) and 9 clients with ASD who were treated in a clinical setting from 1993–2008 (p. 65). Data from Thomson et al. (2010) demonstrates that individuals with ASD receiving a biofeedback intervention "responded more appropriately to social cues, were less ego-centric, and displayed reduced anxiety" (p. 79). Participants were connected to an EEG device for measurement of neurofeedback by

the researcher, and provided with outputs from Focus Technology or Thought Technology equipment that presented the participant with biofeedback data such as their HRV and skin temperature (Thompson et al., 2010). The participants were taught diaphragmatic breathing as an intervention to reduce anxiety, and "when adult clients observed how their physiology changed with stress and then how they could control these changes with breathing and muscle relaxation, they typically became enthusiastic about incorporating this BFB into their program" (Thomson et al., 2010, p. 70). This outcome of the Thomson et al. study offers promise that biofeedback training can influence levels of anxiety and is easily accepted by participants.

Scolnick (2010), investigated the effectiveness of an EEG intervention with adolescents diagnosed with AS; however, due to a high dropout rate, no statistically significant findings were available. Those still considered adolescents often dominate the college population. Continued research is needed in adolescents and the college population with AS in order to accumulate enough data for analysis of biofeedback interventions in this population. This study contributes to the literature of those working with this critical population.

Pineda et al. (2008) examined neurofeedback as an intervention tool for attention in children with ASD. Pineda et al. (2008) found that "neurofeedback training has behavioral and electrophysiological consequences for children with ASD" and that, "positive changes in attention, impulsivity, and other assessments of behavior assessed by parents also change" (p. 578). The opportunity for positive behavior changes as a result of biofeedback interventions deserves additional research attention. Biofeedback is a promising intervention in addressing anxiety, and could have other positive effects.

Literature points to the effectiveness of biofeedback for multiple aspects of behavior, but further researcher is needed on behavior changes in specific populations such as individuals with ASD.

Exploratory Data Analysis

A common theme in literature related to ASD is that not enough is known. As a relatively new diagnosis that has experienced rapid growth in awareness and diagnosis, ASD research on higher education, accommodations, mental health, or the impact of CBT or biofeedback is all limited in volume and depth. Tukey's (1977) advocacy for EDA offers a valuable perspective by focusing on the big picture of what data offers, and using graphic tools to identify trends that can guide future research. In fields as new as ASD, the benefit of EDA is that data analysis is not dependent on the formation of strict hypotheses, but instead focuses on what exists in the data and establishes a foundation that can guide specific research in the future.

Behrens (1997) offered a summary of five characteristics that define an EDA approach:

(a) an emphasis on the substantive understanding of data that address the broad question of "what is going on here?" (b) an emphasis on graphic representations of data; (c) a focus on tentative model building and hypothesis generation in an iterative process of model specification, residual analysis, and model respecification; (d) use of robust measures, reexpression, and subset analysis; and (e) positions of skepticism, flexibility, and ecumenism regarding which methods to apply. (p. 131-132).

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In the context of research on biofeedback in college students with ASD, EDA offers an opportunity to explore the first impressions of this new research area and attempt to answer the question of what is going on.

Early EDA advocates such as Hartwig and Dearing (1979) and Tukey (1977) offered strong support for visual representations in addition to descriptive statistics in order to appreciate the full scope of data. Tools such as box-and-whisker, scatter plots, stem-and-leaf, and box plots are still encouraged by more modern EDA advocates such as Behrens (1997) and Cohen (1994). In a particularly critical rebuke of traditional CDA traditions, Cohen (1994) argued that, "even before we, as psychologists, seek to generalize from our data, we must seek to understand and improve them" (p. 1001). Behrens (1997) offered a similar, though softer, offering in expressing that EDA, "allows researchers to build rich mental models of the phenomenon being examined" and, "found EDA useful when there is little explicit theoretical background to guide prediction and the first stages of model building" (p. 154).

EDA provides a framework for the analysis of early stage data where preexisting research and models are only forming. With so little known about the causes, treatments, and rise in diagnosis of ASD, traditional hypothesis testing would be premature. However, ASD biofeedback research is better served through EDA, because EDA will establish foundations upon which to build meaningful models.

College students with ASD have an immediate and critical need for accommodations and interventions that can counteract the incredibly debilitating and dangerous effects of anxiety and comorbid mental health conditions. Limited literature exists on interventions like CBT and newer technology based interventions like HRV

based biofeedback. This research study is able to apply the strengths of an EDA approach to the evaluation of a new technique, biofeedback, in an emerging and underserved population. The literature clearly articulates a need for college students with ASD, promising new interventions, and a tool to evaluate these interventions that offers the most robust and balanced approach to understanding new data.

The literature identifies increased rates of anxiety in individuals with ASD, and documents the threat to QOL and college success for individuals with poor coping skills and high anxiety. Traditional talk therapy models, such as CBT, have limitations in a college environment and new technology is offering alternatives. The literature supports the use of biofeedback as an emerging technology for treating anxiety in individuals with ASD, but no literature addresses the use of biofeedback in a college population with ASD. More research is needed on the effectiveness of biofeedback as an intervention for anxiety in college students with ASD. Because the use of biofeedback in college students with ASD represents a new field of study, a tool to identify possible trends and generate hypotheses is required and EDA is an exceptional framework for this type of data analysis. This study uses EDA to identify trends and evaluate data from a 10-week biofeedback intervention in college students with and without ASD. Implications for future research, the development of hypotheses in the field of ASD and biofeedback, and the use of EDA as a powerful research tool are examined.

Chapter 3

RESEARCH DESIGN AND METHODOLOGY

Introduction

The literature on the accommodation experience of college students with ASD, the role of anxiety on quality of life, co-morbidity of anxiety and ASD, the emergence and effectiveness of biofeedback as an intervention for anxiety, and the use of EDA as a computational tool for program evaluation offer a solid foundation for the research methods included in this chapter. Understanding the critical needs of students with ASD who transition to college, and will likely experience the negative effects of anxiety, shape the interventions such as the biofeedback intervention described below.

Perspective

During the 2011/2012 academic year, the Disability Resource Center (DRC) on the Arizona State University (ASU) Polytechnic campus purchased a biofeedback software program, EmWave Desktop®. DRC staff selected biofeedback specifically to assist students with ASD, because it was affordable, provided hard physiological data in real-time, allowed for solitary and independent use by students, and represented a fun technology-based approach to providing student support. The Director of University Counseling Services and a faculty member in the psychology department both recommended EmWave Desktop® as a platform for conducting biofeedback. The purchase and use of the EmWave software by the DRC was to support students with ASD and was not intended for formal academic research. An image of the EmWave biofeedback device is found in Appendix A.

The psychology faculty member, who recommended EmWave software to the DRC, invited the DRC Director to his introductory psychology courses to present on biofeedback. After class lectures on biofeedback from the DRC Director, the students from two sections of introductory psychology were encouraged to use the biofeedback software in the DRC as a compliment to their coursework.

The DRC introduced a hardcopy data sheet, included as Appendix B, to document the use of EmWave by students with ASD and the introductory psychology students. During participant use of the biofeedback software, data was available in real-time and an onscreen summary was available at the conclusion of each session. From the summary screen, participants recorded session time and HRV scores on the hardcopy student data sheet immediately following each session. The data sheets were stored in the DRC and entered into a single electronic file on the DRCs university server. The data was collected across 10-weeks in a target population, students with ASD, as well as typical peers without ASD.

The DRC did not analyze any biofeedback data prior to participation in this research study. The unanalyzed biofeedback data represented an archival data set with important implications for the use of biofeedback in college students with and without ASD. The ASU DRC and the Institutional Review Board (IRB) of ASU approved the use of this data for analyses. This research study used an exploratory data analysis (EDA) approach in the evaluation and analysis of DRC biofeedback data.

Context

A review of the literature identified college students with ASD as an emerging and underserved population in higher education; however, the literature did not

adequately address interventions for high rates of anxiety in college students with ASD. Literature did support the use of biofeedback as an intervention for anxiety, but the literature did not evaluate the use of biofeedback in college students with ASD. Disability professionals in higher education are in immediate need of new tools, like biofeedback, to serve students with ASD.

Data Analysis

This study used EDA approach to analyze the DRC biofeedback program. EDA is a valuable approach to program evaluation and reveals trends and hypothesis that conventional methods overlook (Behrens, 1997; Cohen, 1994; Sinacore, Chang, & Falconer, 1992). Sinacore et al. (1992) used EDA in the evaluation of two groups receiving treatment for rheumatoid arthritis. EDA revealed nuances in the data that conventional hypothesis testing had missed, that one group lagged the other until 18 months of treatment at which point the groups shared common outcomes (Sinacore et al., 1992). The findings of Sinacore et al. are consistent with other literature on EDA that identifies EDA as a tool for establishing a foundation for specific hypothesis testing and provides the researcher with greater holistic understanding of the data (Behrens, 1997; Cohen, 1994; Sinacore, Chang, & Falconer, 1992; Tukey, 1977). A lack of prior research on the populations and interventions presented in Sinacore et al. meant that hypothesis testing was not as valuable as EDA because not enough was known about the data set to justify the testing of hypotheses.

The DRC data set was similar to Sinacore et al. (1992) in that no prior research existed on biofeedback in college students with ASD; therefore, the creation and testing of hypotheses was not as valuable as a thorough examination of the data for the

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identification of hypotheses to guide future research (Behrens, 1997; Cohen 1994). Rather than design a pre and post-test to evaluate the use of biofeedback in college students with ASD in a traditional CDA approach, using EDA offered a valuable summary of the data and relevant trends and provided meaningful direction for future interventions and research designs.

The descriptive statistics used in EDA will provide a valuable summary of the DRC biofeedback program and can assist with justification for the continuation or adaptation of the program. The use of simple graphics, such as histograms and box plots, will offer the DRC a practical, immediate, and functional evaluation of their program. Additionally, the hypotheses generated by the EDA approach will contribute to future research and practice in the use of biofeedback in the emerging and at risk population of college students with ASD.

Participants

In January 2012, students with ASD and students in two introductory psychology courses were invited to use biofeedback software in the DRC. Disability Access Consultants (DAC) serve as advisors to students with ASD at the university. DACs identified their most anxious students with ASD and recommended that they use the biofeedback software for 10 consecutive weeks. Students in two sections of Introduction to Psychology (PGS 101) were invited to use the software by the DRC Director following class presentations on biofeedback.

The DRC collected biofeedback data from 47 (N=47) participants. Of the 47 total participants, 37 were typical students recruited from PGS 101 (n=37) and 10 students with ASD (n=10) were recruited by their DACs. More males participated than females

with 38 male participants and 9 female participants. Specific demographic information such as race and age were not available with this data set; however, all participants were currently enrolled undergraduate students at the time of data collection.

Instruments

HRV data was collected using the EmWave® Desktop heart-monitoring computer software system. The DRC selected EmWave® Desktop based on recommendations from both the Director of University Counseling Services and a psychology faculty member who were familiar with the product. EmWave® Desktop has been used in other biofeedback studies such as Beckham, Greene, and Meltzer-Brody (2013) and Henriques, Keffer, Abrahamson, and Horst (2011). HRV data is collected by EmWave® Desktop via a USB sensor worn by the participant and displays real-time HRV information in an on-screen graphical format. The display allows participants to view their progress in real-time. Participants are able to independently begin and end biofeedback sessions and complete HRV data is available after every session. Additional information on EmWave® Desktop is available through the EmWave website (http://www.heartmathstore.com/item/6020/emwave-desktop-stress-relief).

Procedure

The procedure for data collection was standardized by the DRC. Every biofeedback session occurred in a private room located in the DRC office suite on campus. Individual biofeedback sessions occurred during regular business hours of 8am-5pm Monday through Friday. For the first session, DRC staff assisted participants in loading the software and connecting the USB sensor. EmWave is designed to be used independently. Strengths of the EmWave software include provision of a standard

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tutorial, on-screen directions for use, and automatic calibration of the USB sensor before every new session. After the initial session, all future sessions were completed individually by participants independently. Participants using the EmWave software were encouraged by DRC staff to complete a 10-minute session once a week for 10 weeks with no less than 72 hours between sessions. After the initial session with DRC staff assisting participants with loading and starting the software, participants independently completed future sessions in the DRC. Participants recorded the date, length, and HRV scores of every session on a data sheet stored in the DRC.

Summary

The biofeedback program at Arizona State University's Polytechnic campus offered an opportunity to evaluate a biofeedback intervention in college students with ASD alongside typical peers. Using EDA to evaluate the program allows for the greatest contribution from the collected data despite a small sample size and lack of previous research in this area.

Chapter 4

RESULTS AND DISCUSSION

The purpose of this study was to evaluate the use of biofeedback in 36 university students without ASD and 10 university students with ASD who engaged in a 10 week biofeedback intervention. Biofeedback has been used as an intervention for individuals suffering from anxiety, and increasingly as an intervention for individuals with ASD (Friedman & Thayer, 1997; Hammond, 2005; Linden, & Myers, 2009; Reiner, 2008). Until this study, no literature existed on the use of biofeedback in a college ASD population or compared a typical college biofeedback user to a college biofeedback user diagnosed with ASD. Due to the novelty of the intervention in this study, EDA was selected for the analysis of research data in order to build a foundation of knowledge in this field (Behrens, 1997; Cohen, 1994; Tukey, 1977). The results and subsequent discussion of the findings represent a significant contribution to two emerging fields of study - ASD and biofeedback.

EDA approaches data analysis with the goal of understanding basic trends, tenets, and themes of data through a highly visual approach. The results reported in this chapter adhere to the EDA philosophy and represent information identified by the researcher through the process of data entry of physical participant data sheets, as well as the use of descriptive statistics and graphing techniques applied to the data once inputted into a spreadsheet. EDA cannot, and does not, imply statistical significance for findings; however, the results are intended to guide ideas about research and influence the development of models and future research design.

Results and Discussion

Given the freedom that EDA allows and encourages in data analysis, three broad themes were developed to guide this research process. The three themes explored the following: data trends between the two research groups, data trends within each group, and trends across the research study as a whole. In exploring these concepts with EDA, additional trends emerged and were explored. The research data was segmented into the first five weeks and second five weeks and trends between and within the two research groups were explored using this framework. The goal of this study was to provide a foundation for future research on the use of biofeedback in college populations, specifically as an intervention for college students with ASD who are at greater risk for anxiety.

Between Group Trends

Presented with individual HRV coherence scores for participants from the ASD group (n=10) and the Typical group (n=36), comparisons between groups and within groups HRV scores offer initial insight into possible trends of biofeedback as an intervention. Table 1 summarizes the mean scores, time that users spent in an optimal HRV coherence state, for the 10 week duration of the study. A higher mean score indicates a lower HRV and greater control over anxiety.

Table 1

Mean HRV Coherence Score of Participants

Week	ASD	Typical
1	47.80	45.86
2	48.20	39.41
3	39.33	52.40
4	48.13	45.10
5	43.12	48.14
6	47.57	47.25
7	58.42	45.77
8	50.83	43.14
9	54.50	47.00
10	38.16	51.70

Data in Table 1 offers multiple first impressions. First, the ASD group mean in Week 1 is higher than that of the Typical group in Week 1. This higher mean remains in effect through the second week of the study. Second, the range of mean scores for both groups appears to show little variance over the course of the 10 weeks with a minimum score of 38.16 and a maximum score of 58.42. The narrow range of scores are line with Scolnick (2010) who identified minimal changes in an ASD group using biofeedback. The minimum and maximum scores were both generated by the ASD group. Table 1 shows that during the final week of the study, Week 10, the ASD mean was lower than the Typical mean in contrast with Week 1. The ASD score in Week 10 is lower than the group's Week 1 score, which is the opposite of the Typical group whose Week 10 score is higher than Week 1.

Existing research documents an increased risk for anxiety in individuals with ASD (Ghaziuddin et al., 2002; Kim et al., 2000; MacNeil, 2009). In this study, participants with ASD were referred for participation by their DAC, staff members who were instructed to make the referral based on the perceived need for an intervention to address anxiety. The first discovery of this study was that during the first biofeedback session in week 1, the mean HRV score for the ASD group was 47.80 compared to 45.86 for the Typical group. Earlier research predicts that the ASD group would display greater anxiety in week 1, indicated by a lower HRV score, than their typical peers; however, the opposite was true.

One reason for this finding may be that students in the introductory psychology course who volunteered for the study were suffering from anxiety and seeking assistance by participating. This interpretation would lead to an elevated initial reading for the typical population and may indicate they are not representative of the typical college student. Similarly, because students with ASD chose to participate after being referred by their DAC, those who participated may have been particularly well adjusted, as evidenced by their engagement with the disability office, or have already developed coping skills to allow them to persist in college. Due to the limited amount of additional data on participants in this study, to determine the exact factors behind this finding is not possible, but future research should explore the anxiety levels of college students with ASD enrolled with DRC offices compared to those students who do not register with disability services.

Additional findings based on data Table 1 were that the week 10 score of 38.16 was lower for the ASD group than their week 1 score of 47.80. Because a lower score

indicates less regulation of HRV, and greater anxiety, the decrease in score would not be expected based on previous research finding lower anxiety after biofeedback interventions (Coben et al., 2009; Hammond, 2005; Reiner, 2008). The Typical group week 10 score of 51.70 is higher than their week 1 score of 45.86, but only by approximately 6 points. Because EDA does not approach data with the intent of finding statistically significant findings, the comparisons of week 1 and week 10 between the groups in Table 1 were designed to explore possible trends based on earlier research. The observed small changes between the groups were not particularly compelling in this format.

Figure 1 provides a visual perspective on the weekly mean HRV scores of the two groups over the 10 week study period. Some of the trends identified from the raw data in Table 1 are also evident in Figure 1. Examples include the higher initial mean for the ASD group in Week 1, the higher mean for the typical group vs. the ASD group in Week 10, and the fairly narrow range of mean scores over the 10 week study period. The higher mean of the ASD group is in contrast with Glennon (2001) and VanBergeijk et al. (2008) who both documented higher levels of anxiety in an ASD population compared to typical peers. In this study, the higher mean of the ASD group suggests a lower rate of anxiety than typical peers.
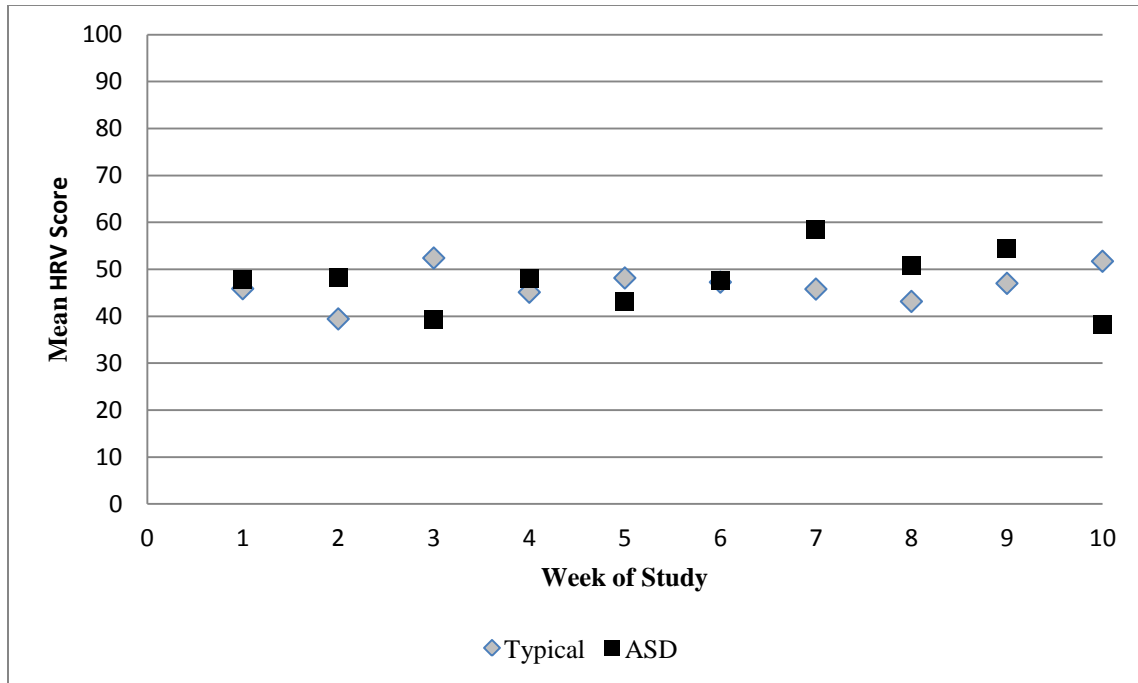
Figure 1. Mean HRV Score by Week of Study.

Figure 2 connects the individual weekly means for the two groups and provides greater visual clarity on trends that may exist. Using different graphical tools to explore data can expose trends in the data (Tukey, 1977). The line plot in Figure 2 exposes the elevated HRV scores for the ASD group in consecutive weeks 7, 8, and 9. These are the only weeks for which the ASD group had optimal HRV scores for the majority of their session time. In Figure 2, weeks 7-9 clearly show some of the highest mean scores for the ASD group, and the scores remain above the Typical group for this three week period. The addition of a trend line in Figure 2 also reinforces the narrow range of scores between the two groups with the exception of weeks 7-9 as already noted. Weeks 7-9 in the ASD group suggest a pattern of improvement similar to McCraty et al. (1998) and Thompson et al. (2010) who found improvements over time in groups using HRV biofeedback interventions.
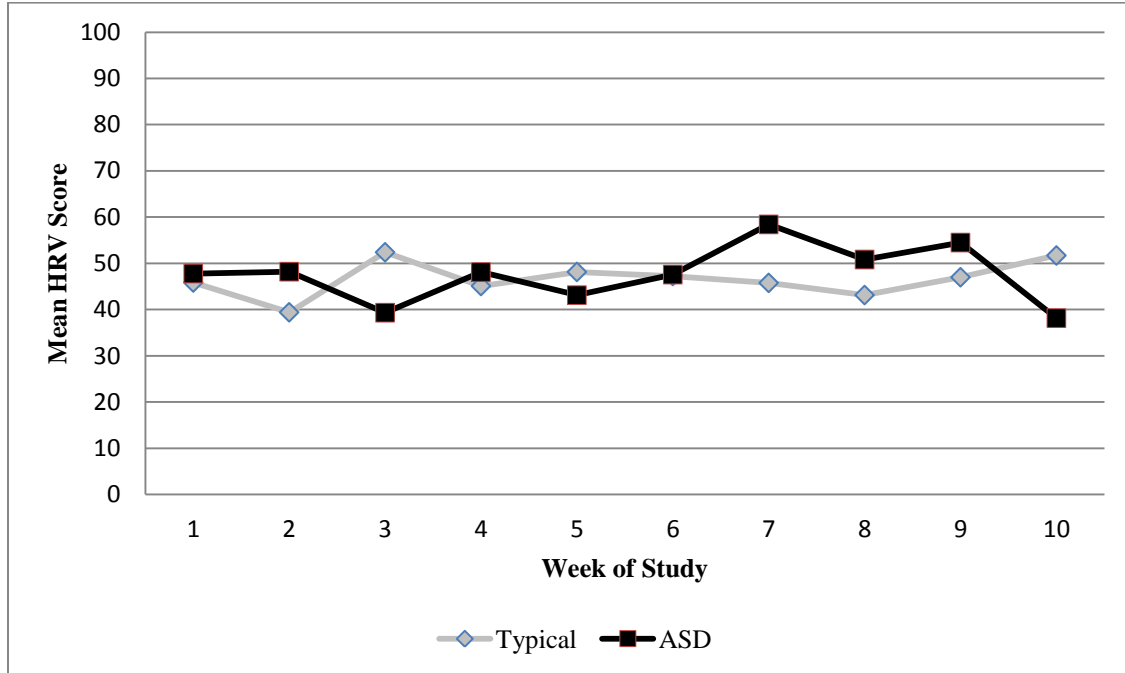
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Figure 2. Mean HRV Scores by Week of Study.

Within Group 10 Week Trends

Because mean HRV scores are based on percentage of time spent in an optimal HRV state, the corresponding time spent in a suboptimal HRV state can also be observed. The method of presentation in Table 1, Figure 1, and Figure 2 do not allow a clear picture of the possible changes taking place within each group over the course of the 10 weeks. Figure 3 adds the suboptimal HRV mean scores in addition to the optimal mean scores for the ASD group.
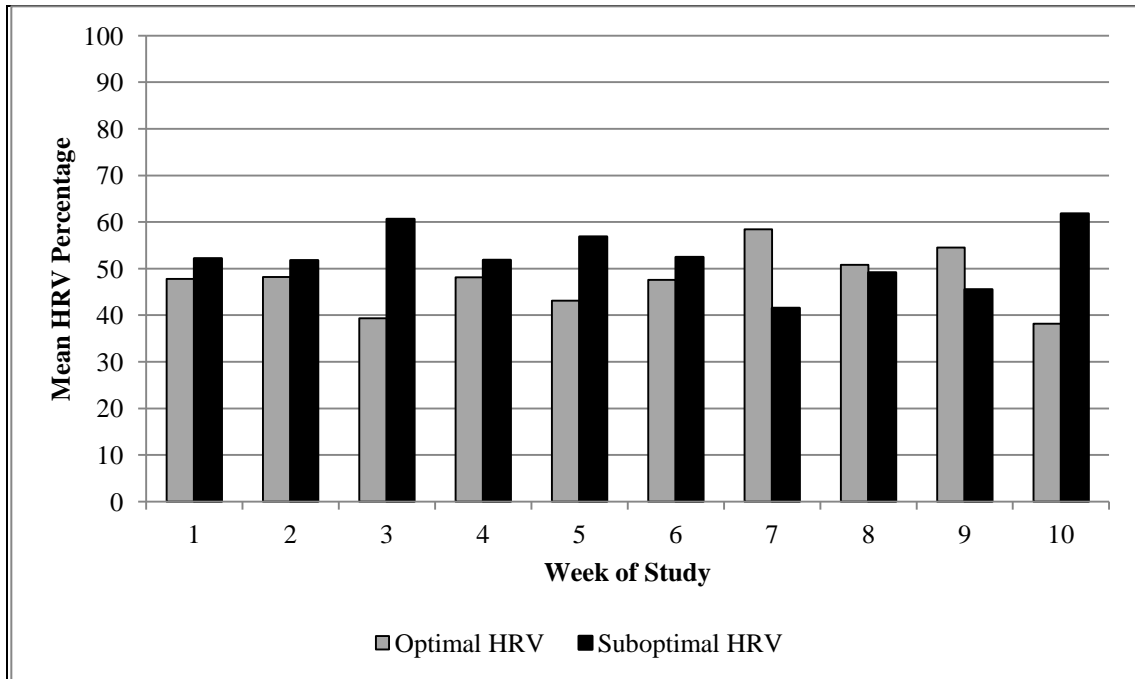
Figure 3. Mean HRV Percentages for ASD Group by Week of Study.

The introduction of suboptimal means in Figure 3 generates a useful contrast in the exploration of the ASD group's week by week means. The bar chart in Figure 3, which shows only the ASD scores, provides confirmation for the finding in Figure 2, but also identifies weeks 1 and 2 and weeks 3 and 10 as having similar visual characteristics. Figure 3 easily identifies that weeks 7-9 were the only weeks where ASD participants spent the majority of their biofeedback session in a state of optimal HRV. This means that for the ASD group, 30% of their sessions were spent with the majority of time in a state of optimal HRV and 70% of sessions in a majority suboptimal HRV state. In the ASD group the three optimal sessions all occurred consecutively. A final observation from Figure 3 is that some weeks appear to match throughout the study. Week1 and week 2 share a resemblance as do week 3 and week 10. McCraty et al. (1998) found that HRV interventions caused individuals to "reprogram" their responses to stimuli and the

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consistent patterns of weeks in this study may represent a reprogramming of participant

responses as a result of biofeedback training (p. 167).

Figure 4 applies the same technique used in Figure 3, but looks only at the

Typical group instead of the ASD group. The only weeks in Figure 4 with a majority of

time spent in an optimal HRV state are week 3 and week 10. Unlike figure 3 where the

ASD group had three consecutive weeks of optimal performance, the Typical group

displays only two occurrences separated by seven weeks. Only 20% of the Typical group

sessions spent the majority of time in an optimal HRV state compared to 30% for the

ASD group. Appelhans and Lueken (2006) found that HRV was a predictor of future

anxiety as well as a real-time marker of anxiety. Based on Appelhans and Lueken (2006)

and Friedman and Thayer (1997), the high levels of suboptimal HRV scores for both

groups in this study may indicate the presence of high levels of anxiety in both groups

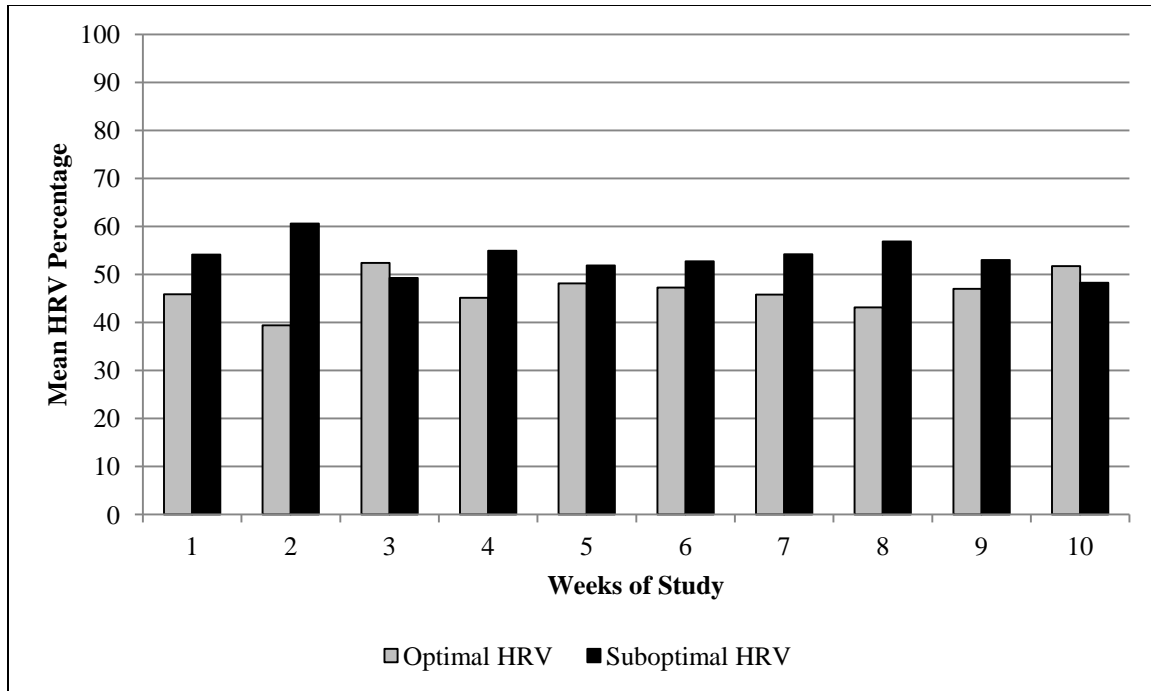that are largely unchanged as a result of the intervention.

Figure 4. Mean HRV Percentages for Typical Group by Week of Study.

Observations from Figure 2, Figure 3, and Figure 4 suggest that individuals with

ASD may be more likely to present consistent HRV patterns compared to a typical

population; the ASD population had a greater number of weeks with majority optimal

HRV scores - three weeks as compared to two weeks in the Typical group, and that the

ASD group's high scores fell in consecutive weeks in three of the final four weeks of the

study compared to the Typical group with high scores in week 3 and week 10. Although

not statistically significant, the consecutive high scores for the ASD group may be

evidence that the intervention had taken hold and participants in the ASD group were

developing better control of their HRV and anxiety.

Multiple approaches are required in EDA to account for the appropriate level of

exploration in establishing a foundation for future research. Although earlier discussion

on between group trends focused on weekly means for the two groups in Table 1, the

mean values discount the large amount of individual data points in each group. The box

plots in Figures 5 and 6 allow a visual display of the complete data for both groups. The

comparison of ASD group data in Figure 5 with the Typical group data in Figure 6 yields

several interesting discoveries.

Although weekly means for the ASD and Typical group are useful in examining

some trends, the use of means does not provide a complete picture of all the individual

data points and unique participant experiences in this study. To address this, Figure 5

uses a box plot for representing the weekly scores of individual participants in the ASD

group. A common EDA tool, the box plot in Figure 5 easily captures the full range of

scores for each week in addition to the median, upper quartile, and lower quartile. An

immediate difference between Figure 2 and Figure 5 is the range of scores. Table 1,

Figure 1, and Figure 2 presented participants' weekly scores as a single weekly mean. As

a result, the range of scores was relatively small when compared with the full range of

scores accessible via the box plot in Figure 5. The identification of different data trends

through the use of multiple graphical tools is consistent with the use of EDA in Sincacore

et al. (1992) and Cohen (1994).

Figure 5 also sheds light on weeks 7-9 for the ASD group during which the

participants' spent the majority of their session in the optimal state. The box plot reveals

a change in the minimum values for the final weeks of the study relative to the early

weeks of the study. The box representing the median and quartiles also changes

dramatically in the final weeks of the study for the ASD group with shrinking quartiles

and consistently elevated medians relative to earlier weeks. Even week 10, which was

suboptimal, shows an elevated median value above earlier weeks. The use of the boxplot

in Figure 5 is based on findings of Tukey (1977) and Hartwig and Dearing (1979) who

both argued for the use of descriptive statistic techniques, such as the box plot, in the
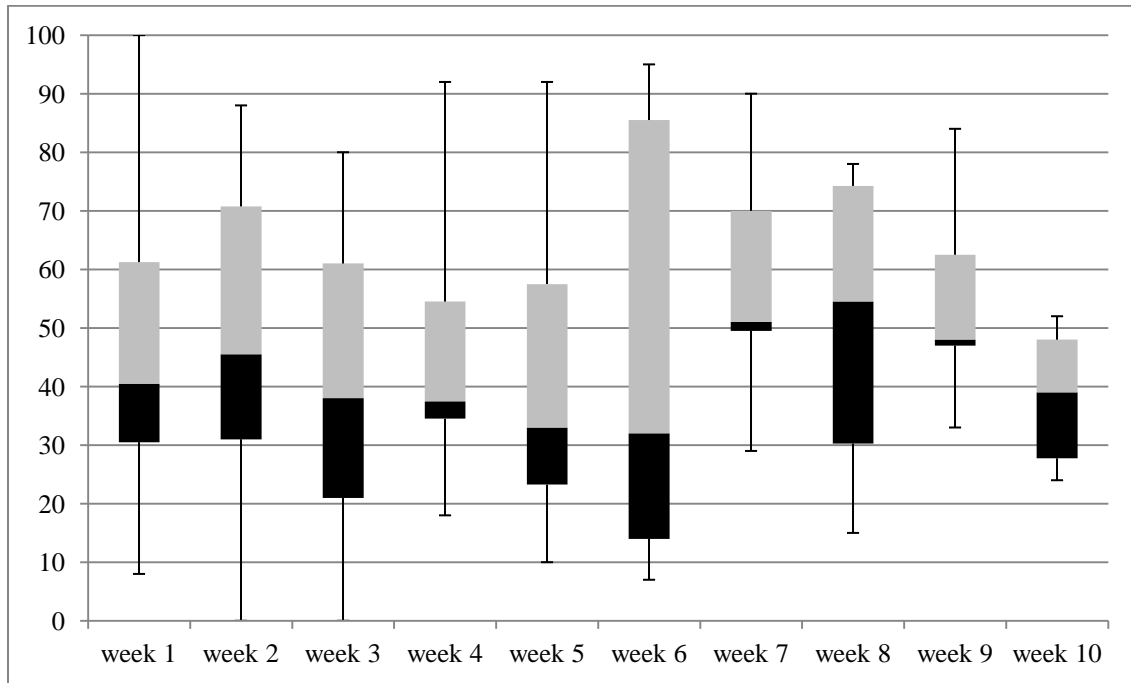
identification of trends in data.

Figure 5. Box Plot of ASD Participant Data by Study Weeks.

Figure 6 uses the same technique as Figure 5, but explores the full data of the

Typical group during the study. Similar to Figure 5, the data range in Figure 6 is striking

with whiskers in both directions creating a range every week that encompasses almost the

entire available data range of 0-100. Compared to the ASD group, the box plots for the

Typical group appear to show more even distributions on a weekly basis than the ASD

group. Whereas Figure 5 showed a trend in rising median values over the final weeks of

the study for the ASD group, Figure 6 does not appear to show any consistent or

available trend in median values. Inconsistency in response to HRV is documented by

previous research, such as Thomson et al. (2010) who identified improvements in HRV

over time and Scolnick (2010) who found little change in HRV over time in a separate intervention. Like Thomson et al. (2010) this study examined an ASD population and similar to Scolnick (2010) small sample sizes may be responsible for inconsistency in the data trends.
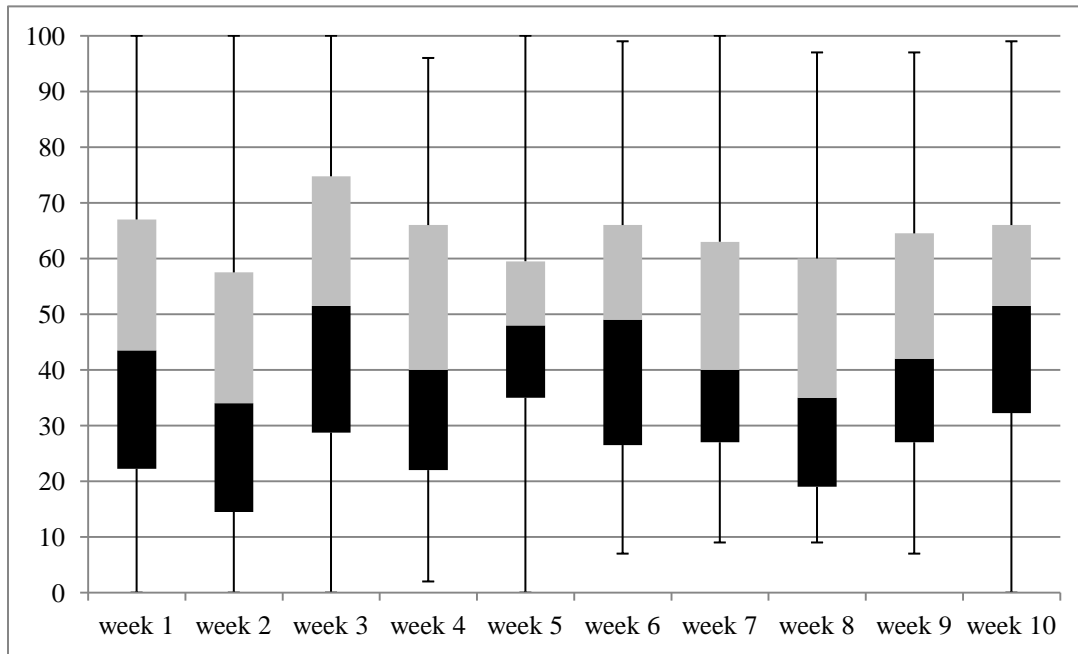

Figure 6. Box Plot of Typical Participant Data by Study Weeks.

Box plot data for the ASD group shows a tighter range of scores than the Typical group, whose scores almost consistently encompass the entire 0-100 range every week. One reason for this difference between the groups could be the larger sample size (n=36) in the Typical group compared to the ASD group (n=10). The greater number of participants in the Typical group may be responsible for the increase in outliers.

In Figure 5, starting in week 7 the ASD group range narrows compared to earlier weeks and may show greater control over HRV or reflect a smaller sample size due to attrition as the study progressed. Sample size could also be a factor in the normal distributions of the weekly box plot data in Figure 6 compared to Figure 5. Weeks 7-10 in

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the ASD group again stand out in Figure 5. This time the median values of 51, 54.5, 48, and 39 for weeks 7-10 are some of the highest median values in the study and appear to show an upward trend in the ASD group data at the end of the intervention.

Overall, between group comparisons using multiple visual platforms identified five possible trends. First, the ASD group showed improved HRV scores in the final four weeks of the intervention. A second trend was that a smaller range of scores was present in the ASD group than the Typical group. A third trend was the identification of a more normal distribution of scores in the typical group than ASD group. The fourth trend identified that the ASD group had a greater number of weeks, three, with an optimal HRV score compared to two weeks in the Typical group. Finally, a narrow band of scores in Figure 1 and Figure 2 highlight that although individual differences were present in participants, the overall differences between the groups was minimal. Figure 2 shows that mean scores for both groups fall between 30 and 60 with little overall fluctuation.

Between Group 5 Week Trends

One of the first instincts in evaluating the study data was to compare the week 1 value with the week 10 value for both groups. A traditional pre-test and post-test design might have even used these specific data points to determine statistical significance. Because the intervention in this study was designed to generate a change in the participants over time, the data analysis should also investigate trends in the data over time. In looking at the variability of the data on a week by week basis for both groups, assigning critical importance to a single week in isolation would be premature. EDA allows trends to emerge, and the data was examined for changes over time that did not rely solely on specific weeks to make determinations about change. Ultimately, the

framework that emerged was to divide the data into the first five weeks, weeks 1-5, and the second five weeks, weeks 6-10. Using this new construct allowed for some analysis of the change over time without being dependent on specific weeks.

This EDA approach is consistent with Sinacore et al. (1992) who identified that hypothesis testing could obscure trends that EDA was successfully able to identify. The flexibility of EDA in this study is supported by Tukey (1977) and Sinacore et al. (1992), and allowed for the first five vs. second five weeks design to emerge from the data

Table 2 provides valuable information to guide the analysis of the data for changes over time while respecting that individual weeks have a high degree of variability. Rather than using week 1 and week 10 the data is divided into weeks 1-5 and weeks 6-10. This approach is similar to that of Sinacore et al. (1992) and their identification of an 18 week tipping point in data trends. The mean scores for the first five vs. second five weeks, along with a total mean for the 5 week periods is included in Table 2.

Table 2

Mean Participant HRV Scores Weeks 1-5 and 6-10

Week	ASD	Typical	Week	ASD	Typical
1	47.80	45.86	6	47.57	47.25
2	48.20	39.41	7	58.42	45.77
3	39.33	52.40	8	50.83	43.14
4	48.13	45.10	9	54.50	47.00
5	43.12	48.14	10	38.16	51.70
Mean	**45.32**	**46.18**	**Mean**	**49.9**	**46.97**

The 10 week study provided a natural break at the five week point to divide the data into two new data sets. Tukey (1977), Cohen (1994), and Behrens (1977) all

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promote EDA as a tool that allows for the data to provide researchers with flexibility in the pursuit of trends and patterns. For this study, the EDA approach allowed for the five week vs. five week model to emerge. As with Table 1, information is available from the raw data itself. The ASD group saw an increase in their mean HRV score from the first five weeks to the second five weeks as did the Typical group. The ASD group's initial mean score for the first five weeks was lower than the Typical group, but this is reversed at the end of the second five weeks with the ASD group posting a higher second five week mean score than the Typical group. The study data viewed in first five vs. second five week increments aligns more closely with the positive change in HRV found in Thomson et al. (2010), Reiner (2008), Corben et al. (2009) and McCraty et al. (1998).

Figure 7 is graphical representation of the first and second five week means by group. Each group clearly makes gains in the second five weeks compared to the first, although they are small. Figure 7 does not offer too much more compared to Table 2 because the amount of individual data has been compressed even more than in earlier
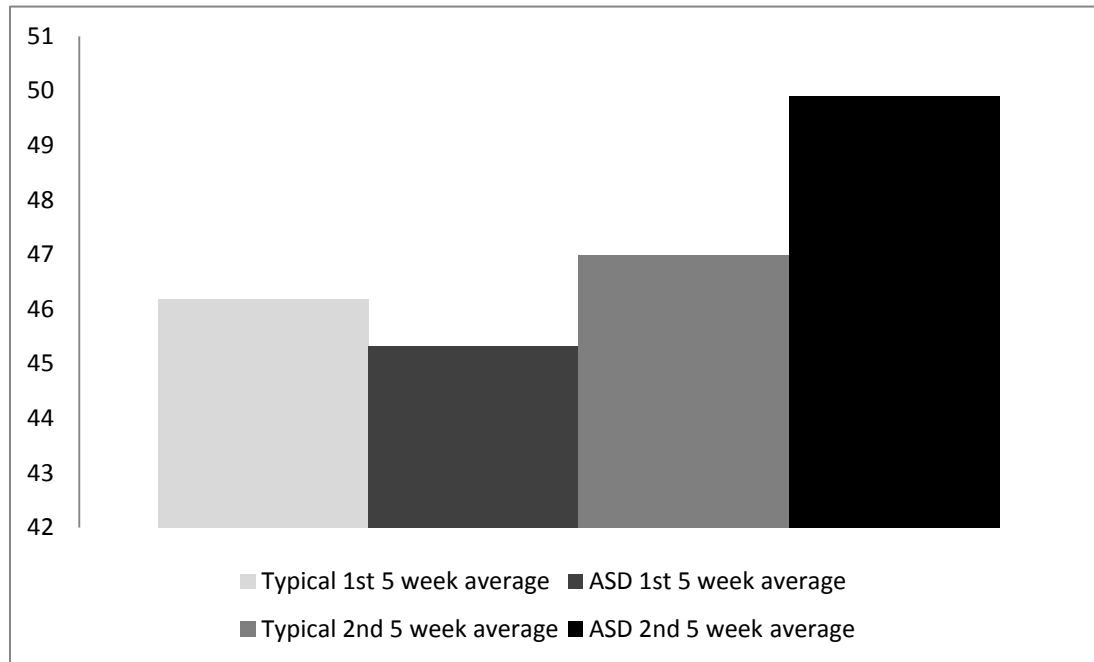
charts.

Figure 7. Five Week HRV Score Means by Group.

Table 2 introduced the means from the first and second five week periods. Several trends became apparent in analyzing this data. Both groups showed gains in HRV mean scores. The ASD group improved from 45.32 to 49.9 and the Typical group improved from 46.18 to 46.97. The ASD group gain of 4.58 is clearly larger than the .49 gain by the Typical group; however, both of these gains remain small. Figure 7 does not provide too much more information than Table 2. Figure 8 provides additional details using box and whiskers.

Figure 8 provides box plots for the two study groups as compared to each other in the first five weeks and second five weeks. Again, the influence of EDA is evident in the use of box plots to graphically represent the data as well as the categorizing of the data into the first vs. second five weeks. Behrens (1997) offered five strengths of EDA, one of which was the, "use of robust measures, reexpression, and subset analysis" an example of

which is on display in Figure 8 (p.132). The Typical group shows an even distribution in the first five weeks with a large range. In contrast, the ASD group shows an uneven distribution with a narrower range. In the second five weeks the Typical group no longer has a normal distribution, but maintains a large range of scores. The ASD group does have a normal distribution on the second five weeks and an even narrower range of scores. Another piece of information in Figure 8 is that the median score in the ASD group increases from the first five weeks to the second, while the median score falls in the Typical group.
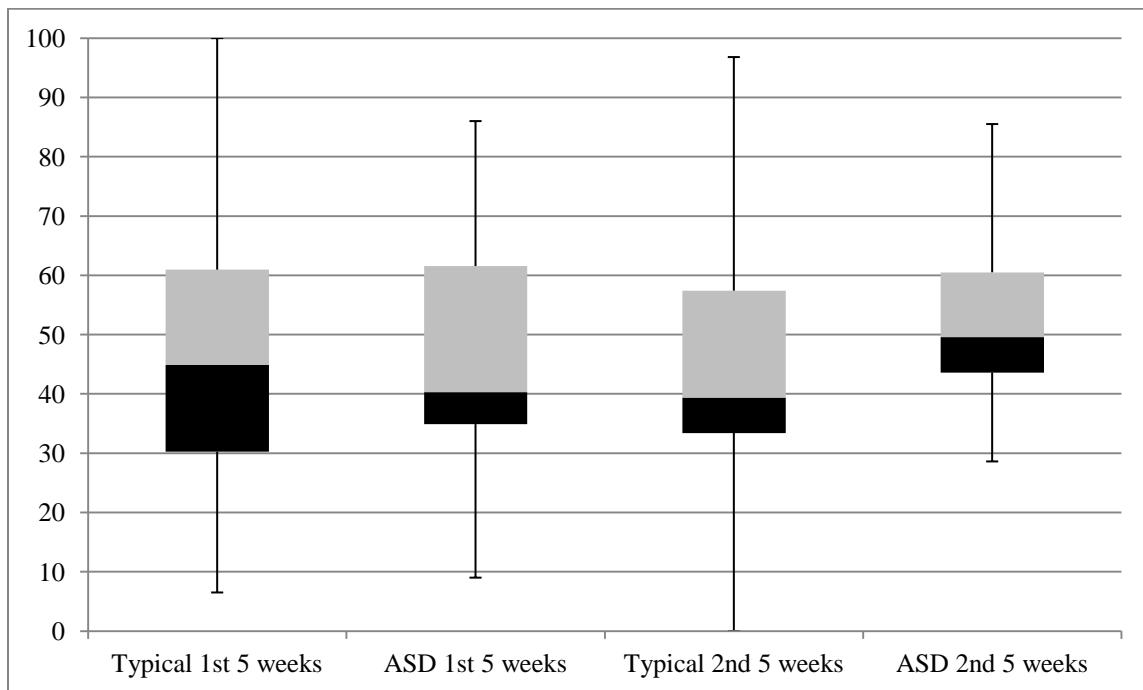

Figure 8. Box Plots for ASD and Typical Groups by First Five Weeks and Second Five Weeks.

In Figure 8, the Typical group has a much larger range with a minimum of 6.5 in the first five weeks and 0 in the second five weeks. The maximum values for the two periods were 100 and 96.8 respectively. The range for the ASD group was smaller in both

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the first five weeks and the second five weeks than the Typical group, but particularly small in the second five weeks compared to the Typical group with a minimum value of 28.6 and a maximum value of 85.5. Again, the range for these groups may be because of the sample sizes at work, but could also be influenced by a greater control of HRV by members of the ASD group.

The other interesting five week vs. five week trend that Figure 8 identifies is the change in median value for the two groups. The median value climbs in the ASD group from 40.3 in the first five weeks to 49.6 in the second five weeks. This finding contrasts with the decline in the median values for the Typical group, which dropped from 44.9 to 39.4. The power of EDA is that multiple perspectives are presented. In this case, the use of different graphical representations and descriptive statistics identified the trend of the ASD group seeing greater improvement than the Typical group when comparing the first five weeks to the second five weeks.

Trends in Participant Attrition

A data trend that was explored through EDA was the pattern of participant attrition. This trend emerged from working with the entire data set and did not evolve from a specific group or between group comparison. As data was entered for this study and processed for analysis, the role of participant attrition on the results became a clear factor. Because the sample sizes began as relatively small, the ASD group starting with 10 participants and ending with only 6 meant that the data was subject to sizeable changes. Using EDA led to a deeper trend within the data that only emerged after deleting participants from data sheet after their last week of attendance. This process

suggested that a relationship might exist between a participant's last biofeedback session and their decision to quit the study.

Several graphical tools were used to evaluate the trend of attrition on this study. Figure 9 offers a visual of how the percentage of participants declined by group over the 10 week study. The Typical group lost participants in the second week while the ASD group lost their first participant in the third week. Both groups display a consistent decline in participation with the Typical group leveling off around the 75% participation rate before a steep decline in the final week. The ASD group ended the study with 60% of the initial participants engaged and the Typical group concluded week 10 with 66% of participants still engaged in the study. This study shared similarities with Scolnick (2010), such as small sample sizes and participant attrition; however, this study uses EDA to examine the specifics of participant attrition that was absent in Scolnick (2010).
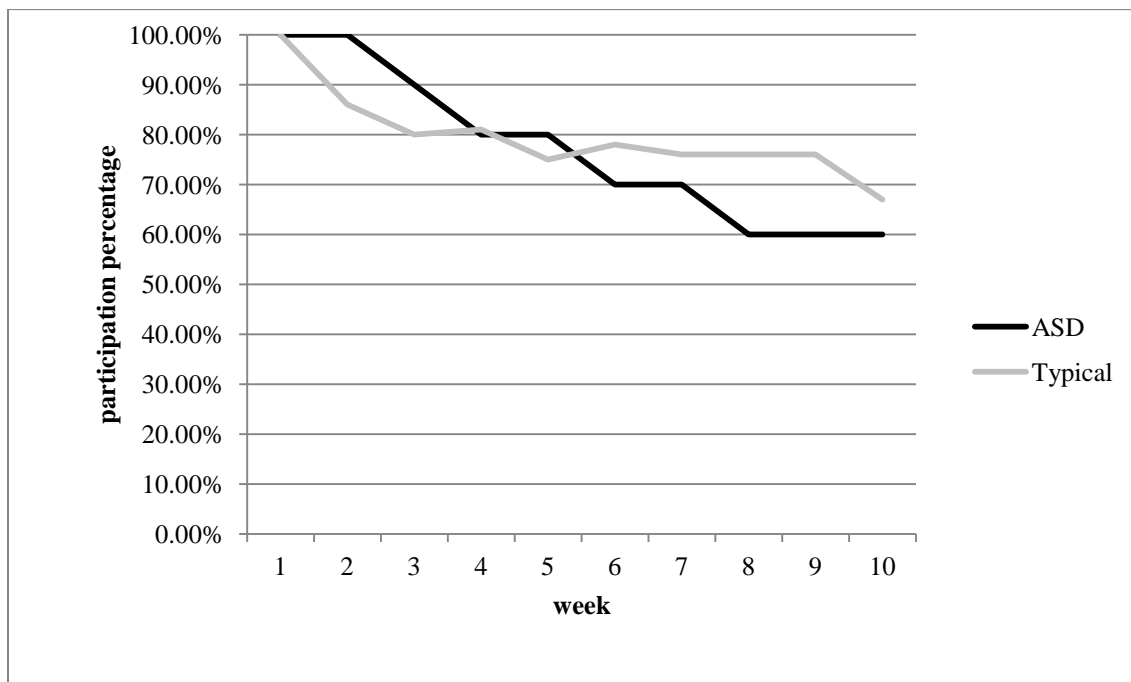

Figure 9. Participant Attrition by Week.

A unique aspect of biofeedback in this study is that the participants completed their sessions independently and without intervention from staff or other sources. In working with the attrition data there was an opportunity to graph the relationship between the week of attrition and the final HRV coherence score in the week prior to attrition. Figure 10 is a scatter plot of participants' suboptimal HRV scores from the week before a participant left the study. In figure 10, a higher y-axis value indicates poor HRV and is plotted against the week they withdrew on the x-axis. Behrens (1997) included an explanation for EDA of which one of the primary goals was to understand, "what is going on here" in the context of a data set (p. 131). This study shared that approach in asking the question of what was going on in relation to participant attrition, and used Figure 10 to help answer that question.

Figure 10 offers some interesting trends. First, a cluster of participants leaves the study in the first three weeks. Of those leaving the study in the early weeks, the HRV scores appear to cluster both low and high with no scores occurring between 31 and 71 despite a mean score for this period around 50. The only participants to leave during weeks 4-8 all had scores below 60 with four participants below 20 and one outlier at 57. The final week of the study saw three participants leave with a range of scores from 90 to 19. If Scolnick (2010) had used an EDA approach or reported on the attrition trends of participants future research would be able to design more effective interventions or test specific hypotheses.
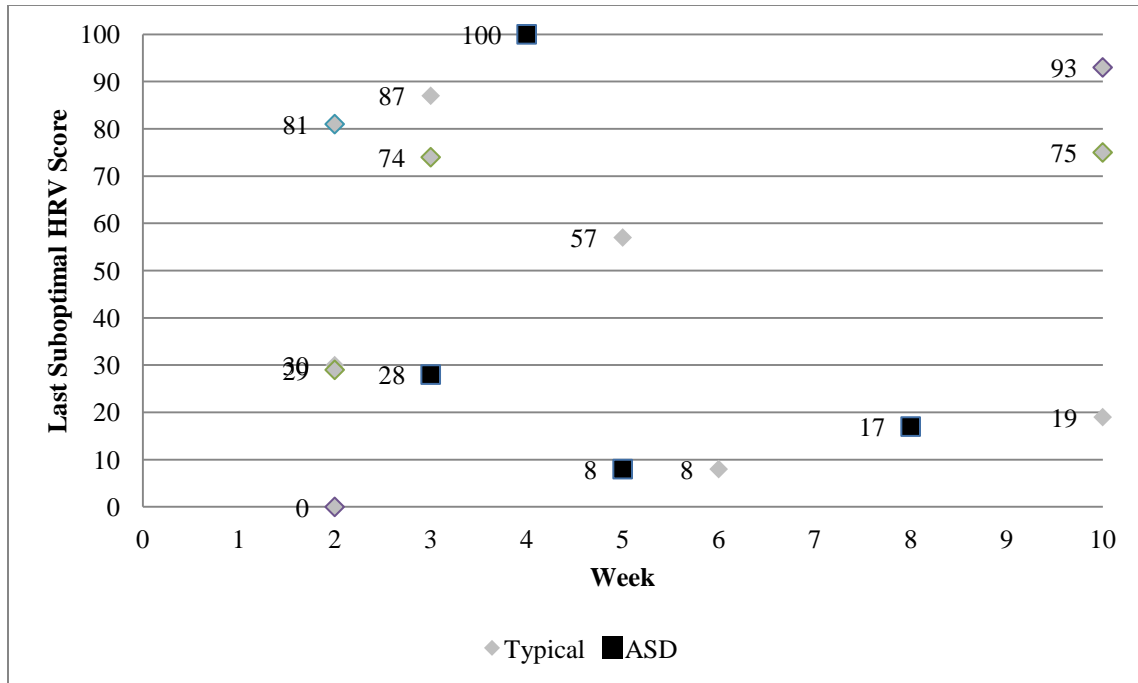
Figure 10. Scatter plot of Participant Attrition by Suboptimal HRV Score and Week.

As would be expected, participants exited the study over the course of the 10

weeks. Figure 10 is a scatter plot that charts the week a participant exited the study with

their last suboptimal HRV score provided to the participant by the biofeedback software.

In week 2, for example, a typical student received a score of 81% in the suboptimal range

and 19% in the optimal range for HRV from the software. Unlike a psychologist

providing cognitive behavioral therapy, the biofeedback software used in this study does

not provide any intervention to a participant who performs poorly. Someone who

received a poor score might be expected to choose not to return because he or she felt the

program was not working.

In studying Figure 10, participants left the study between weeks 1-3 and not in

any great numbers for the remainder of the study until the final week. For those who had

low scores such as 0, 8, 8, 17, and 19 they may have made the opposite conclusion than

their high scoring peers. Receiving a positive score, 0% suboptimal and 100% optimal

HRV coherence, might influence a participant not to continue because the program no

longer serves the purpose of relieving anxiety. Figure 10 identifies a critical area for

biofeedback research and that is personal intervention or observation of participant

progress to provide motivation and collect data on the impact of scores on participants.

Limitations

This study has limitations that restrict the scope of the findings. The data set used

in this study represents a rare collection of college student biofeedback data. Although

the data set is valuable due to relative rarity, the sample sizes of the two groups are small

and even smaller after participant attrition. Lack of additional information about

participants in this study is also a limitation. Not knowing the participants' GPA, SAT

scores, or year in college makes determining what additional factors that may be

influencing the data challenge. Are some of the ASD participants, for example, also

engaged in therapy for their anxiety? Perhaps CBT? Are they honors students? Without

additional information about participants, the implications are limited.

Timing is also a limitation of this study. The academic year for students provides

multiple opportunities for high stress environments and events. This study did not control

for students who may have had tests on days when biofeedback data was collected. The

large variability in HRV scores of participants as observed in box plot representations

may be an indication that individual life events may be influencing the data. Although

future research could not control the impact of life events additional data could be

collected from participants to use in conjunction with HRV scores.

The role of the researcher in conjunction with EDA is also a contributing limitation in this study. The researcher spent copious time conducting data entry and preparing the statistics. The data entry process along with knowledge of past biofeedback research, literature on ASD, and the personal experiences of the researcher in this field are all influences on the patterns, trends, and discoveries that emerged through EDA. Because EDA does not test against predetermined hypotheses, a researcher's own experience, expertise, and bias has influenced interpretation of the results. Researcher bias as a limitation is accepted in the use of EDA, and can be seen as strength in the ability of content experts to identify trends in their field of study.

Future Research

This study examined a biofeedback intervention in college students with and without ASD. Prior to this research, no literature existed on the use of biofeedback as an intervention in college students with ASD. At a minimum, future research should continue to build on the existing literature that clearly demonstrated biofeedback to be a successful intervention in individuals with ASD and should address the specific needs of the college ASD population. Because college students with ASD are an emerging population and spread across the country, future research should deliver interventions at multiple institutions in order to generate substantial sample sizes.

A key trend of this research was that results for the ASD group occurred in the final weeks of the 10 week intervention. In designing future research, weeks 7-10 appeared a critical transition time for the students with ASD in adapting to the biofeedback program. Based on these findings, future research should focus on at least 10 week interventions if not longer.

Future research should also explore the combination of CBT and biofeedback in individuals with ASD. As the results of this study revealed, biofeedback can be a useful tool because users can work independently; however, this study identified immediate past session performance as a possible reason for attrition. Monitoring of participant progress and intervening after high or low scores could improve study dropout rates that would maintain larger sample sizes and improve future study data. Most importantly, future research could use biofeedback in conjunction with other measures of anxiety. A simple self-report form for participant stress levels could have been used to correlate HRV scores and may offer valuable research information.

The identification of limitations in this study such as the background of students enrolled and the environmental and personal stressors students may be experiencing are important markers for future research. More information is needed about college students with ASD in order to refine interventions. A challenge facing most researchers is that the populations of greatest concern are the hardest to reach. Those students who enrolled in this study chose to participate after an invitation via class lecture of personal conversation. For those students who are isolated as a result of their anxiety, researchers should develop specific strategies for engaging these students in interventions and evaluating the success of those interventions

This study also serves as a reminder that complicated statistical packages that can test for significance may overlook key trends and discoveries in data sets that are better served through EDA than traditional CDA approaches. Future research will be needed which incorporates lessons from early stage research, such as this study, and tests specific hypotheses that have been vetted through thorough EDA.

Despite the critical juncture facing young adults with ASD who are transitioning to college and need assistance with anxiety, other student populations are also in need of assistance. The population of returning veterans on college campuses is also rising. This population too appears to have issues with anxiety that can also limit their ability to be successful in college. The need to develop sustainable, affordable, and appropriate interventions for college students struggling with anxiety is an immediate need in higher education. This study demonstrates that biofeedback may be one approach that can be used in meeting the anxiety epidemic facing too many students, but research must continue to refine interventions that can create access and opportunity for everyone at the postsecondary level.

Chapter 5

SUMMARY AND CONCLUSIONS

EDA provided a capable framework for the analysis of data in this study. Using the three themes: trends between groups, trends within groups, and trends across groups, discoveries and recommendations for future research were suggested. Between the two groups, the ASD group trended toward improvement in the second five weeks compared to the Typical group, and showed a smaller range of scores than the Typical group. Within each group, the Typical group showed inconsistent HRV scores and no pattern of progress. The ASD group had three consecutive weeks of improved HRV scores and four consecutive weeks of raised median values in the second half of the study. In working with the entire data set, trends emerged related to the attrition and last score received by participants. All of these trends unearthed through EDA techniques will shape future research that will combine additional participant information and measures of anxiety along with greater supervision and professional collaboration to hopefully further the field of biofeedback research in individuals with ASD at the college level.

The energy surrounding ASD and the development of new technologies such as biofeedback offers hope that current students with ASD may have solutions sooner than previous generations of students with disabilities. Research has already laid a foundation for biofeedback as an effective tool in the treatment of anxiety. Because the presence of anxiety in the ASD population is so pervasive and harmful, research has tried in earnest to unlock solutions through traditional CBT and now through biofeedback. Researchers are making progress, and their contributions allow research such as this study to venture into new domains based on the growing body of work in biofeedback and ASD.

Disability service providers are the first ones to experience the wave of new students with ASD entering higher education. Therefore, new interventions for students with ASD will likely continue to emerge from disability service professionals. This study used EDA to explore the results of one university's DRC office intervention designed to address anxiety in a college ASD population. The use of EDA in this study provides a foundation for future research on the use of biofeedback in college students with ASD. Despite small sample sizes and limited details on the participants in this study, the data allowed for initial trends to emerge and the development of new research questions that will guide future practice.

Based on the results of this study future research should build on two key trends identified in this study.

- First, future research should combine supervision of biofeedback progress and allow for intervention, or at a minimum, the collection of data related to attrition of participants.

- Second, the findings related to attrition are a direct result of using EDA and demonstrate the powerful results that descriptive statistics and visual displays can provide when allowed to emerge from data.

Questions that arose in the course of this study are opportunities for future research to build on the findings and discoveries of this study. Key questions from this study include:

- Is biofeedback an effective stand alone intervention for anxiety in college students with ASD?

- How does biofeedback impact anxiety in college students with ASD who do not use support services such as counseling or DRC services?

- Can biofeedback be used by other at-risk or emerging college populations that suffer from anxiety?

The experience of college students with ASD requires additional research. The use of biofeedback as a treatment for anxiety in college students with ASD, and other college populations such as veterans, also requires attention. EDA was used effectively to unearth key trends and discoveries in this study, and should be used with greater frequency by researchers across disciplines.

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APPENDIX A

MANUFACTURER FLYER FOR EmWave® DESKTOP BIOFEEDBACK STYSTEM

De-Stress * Rejuvenate * Perform

emWave Desktop is a scientifically validated hardware/software system that teaches techniques to help you create an optimal state in which the heart, mind and emotions are operating in-sync and balanced. This is achieved through a patented process which displays heart rhythm patterns in real time showing you when you are in this high performance state.
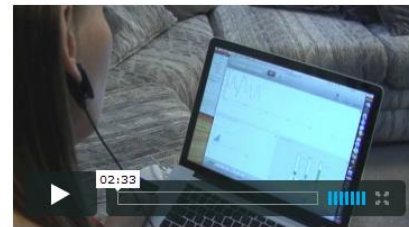
| Features | Benefits | Free Webinar |

The Tools for Success

- Real-Time Heart Rate Variability Monitor
- Four challenge levels to help you raise your baseline coherence levels
- Coherence Coach® tutorial for learning and applying the Quick Coherence® technique
- Interactive Games that help you transform stress into creative energy
- Emotion Visualizer® provides stunning colorful images which vary according to your emotional state and coherence level
- Data storage showing coherence levels for session and history review

EmWave Desktop Promotional Materials. A product summary provided on the manufacturer's website.

Retrieved from http://www.heartmathstore.com/item/6020/emwave-desktop-stress-relief.

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APPENDIX B

SAMPLE FORM FOR DRC BIOFEEDBACK COLLECTION

EmWave Biofeedback

First Name

Last Name

ID#

Class (e.g. PGS 101)

Instructor

Sessions	Date	HRV Red Score	HRV Blue Score	HRV Green Score	Length of session (e.g. 10:00 minutes)
1					
2					
3					
4					
5					
6					
7					
8					
9					
10					

Return this form to the DRC front desk after each session.