

Affective Computing in the Area of Autism

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AFFECTIVE COMPUTING IN THE AREA OF AUTISM

by

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ABSTRACT
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Niharika Jain, B.E., M.S.

Marquette University, 2015

The prevalence rate of Autism Spectrum Disorders (ASD) is increasing at an alarming rate (1 in 68 children). With this increase comes the need of early diagnosis of ASD, timely intervention, and understanding the conditions that could be comorbid to ASD. Understanding co-morbid anxiety and its interaction with emotion comprehension and production in ASD is a growing and multifaceted area of research. Recognizing and producing contingent emotional expressions is a complex task, which is even more difficult for individuals with ASD. First, I investigate the arousal experienced by adolescents with ASD in a group therapy setting. In this study I identify the instances in which the physiological arousal is experienced by adolescents with ASD (“have-it”), see if the facial expressions of these adolescents indicate their arousal (“show-it”), and determine if the adolescents are self-aware of this arousal or not (“know-it”). In order to establish a relationship across these three components of emotion expression and recognition, a multi-modal approach for data collection is utilized. Machine learning techniques are used to determine whether still video images of facial expressions could be used to predict Electrodermal Activity (EDA) data. Implications for the understanding of emotion and social communication difficulties in ASD, as well as future targets for intervention, are discussed. Second, it is hypothesized that a well-designed intervention technique helps in the overall development of children with ASD by improving their level of functioning. I designed and validated a mobile-based intervention designed for teaching social skills to children with ASD. I also evaluated the social skill intervention. Last, I present the research goals behind an mHealth-based screening tool for early diagnosis of ASD in toddlers. The design purpose of this tool is to help people from low-income group, who have limited access to resources. This goal is achieved without burdening the physicians, their staff, and the insurance companies.

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1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a pervasive developmental disorder characterized by deficits in social interaction and communication, and presence of restricted, repetitive behavior (American Psychiatric Association, 2013).. The prevalence rate of this disorder is increasing at an alarming rate. Early diagnosis and timely treatment of this disorder can help improve the quality of life of not just the patients, but also of their primary caregivers, such as parents, family, and friends (Harris & Handleman, 2000; Woodgate, Ateah, & Secco, 2008). Moreover, the development of therapeutic tools can make the treatment more accessible in terms of cost, time, and effort. There are several barriers in early diagnosis (lack of knowledge, resources, etc.) of ASD (Fountain, King, & Bearman, 2011) and timely interventions (need of individualized approaches) (Mesibov, Shea, & Schopler, 2004). In order to overcome these barriers, different solutions are proposed in the form of multi-modal assessment of physiological arousal, a mobile-based social skill intervention and an mHealth based screening tool for assessing the risk of ASD. In the case of ASD, if the interventions are not done in a timely manner, it may give rise to secondary problems like anxiety disorders, obesity, and depression (Curtin, Anderson, Must, & Bandini, 2010; Stewart, Barnard, Pearson, Hasan, & O'Brien, 2006; White, Oswald, Ollendick, & Scahill, 2009). Out of these, anxiety disorders are of grave concern, to an extent that some researchers feel that anxiety may be co-morbid to ASD (Simonoff et al., 2008). These anxiety-related issues affect the overall development of the child (Sukhodolsky et al., 2008) and can distance them from their caregivers (Simonoff et al., 2008).

This dissertation is about three research problems, all of which are centered on ASD. In the first research problem, the instances of physiological arousal (using a multimodal approach) among adolescents with ASD are identified. A relationship between the experience, expression and self-awareness of physiological arousal in these adolescents is established. The data for this study were collected while the participants were attending a social-interaction intervention. The Program for Education and Enrichment of Relational Skills (PEERS) (Laugeson, Frankel, Mogil, & Dillon, 2009) is a social skills training intervention for adolescents and young adults. Although this program in itself has a strong evidence-base for use with teenagers with ASD (Laugeson, Frankel, Gantman, Dillon, & Mogil, 2012), the uniqueness lies in using PEERS with the aim of understanding the emotional expression. In this study, a novel multimodal approach is proposed for looking at the physiology of adolescents with ASD. This study looks at the relationship between “have-it”, “show-it” and “know-it” components of experience and expression of arousal. In the literature, it has been seen that the emotion related studies are usually carried out in lab-settings, which is not really an ideal situation for natural emotions to come out. This limitation was eliminated by collecting data during a group therapy context. A comparison of human understanding of arousal from facial images of adolescents with ASD was done with that of a machine algorithm.

In the second research problem, a mobile-based application for teaching social skills to children with ASD is introduced. Parents of children with ASD report a higher-than-common rate of anxiety disorders (Bitsika & Sharpley, 2004; Gray & Holden, 1992). It has also been shown that addressing parental anxiety is an important piece of addressing anxiety among children with ASD (Conner, Maddox, & White, 2012).

Moreover, the use of technology is sometimes overwhelming for parents or caregivers, who may also be addressing the needs of their children with ASD (Sharpley, Bitsika, & Efremidis, 1997). With the advent of this learning application, we evaluate the tool to see if we were able to provide an effective learning environment for children without putting any burden on the parents or caregivers.

In the last research problem, the design goals for an mHealth (mobile health) based screening tool for ASD are investigated. Several factors, such as lack of awareness, time, and resources create barriers in timely screening of developmental disorders (Sices, Feudtner, McLaughlin, Drotar, & Williams, 2003). Even when a screening for developmental delays is done, there may be a gap in formal diagnosis of ASD, due to the lack of or delay in proper routing to the experts who can perform diagnostic assessments for ASD. Early diagnosis of ASD is fundamental for successful intervention to improve areas of difficulty, and subsequently cause better quality of life. In this study, the development of an effective screening tool is proposed, which not improves early screening of ASD, but also guides the family to a proper diagnostic channel in case of positive screens.

1.1 Outline of the Dissertation

In chapter 2, I present the background information on core concepts: (1) emotions, (2) affective computing, (3) multi-modal affect detection, and (4) ASD. In Chapter 3, I present the approach for studying arousal among children with ASD during an intervention. Chapter 4 examines the human understanding and interpretation of arousal from facial images of adolescents with ASD. Chapter 5 explains the design goals of a mobile-based social skills intervention and the methods applied for validating those

design goals. In chapter 6, I present the groundwork for the development of an automated screening tool for ASD. Finally, in chapter 7, I conclude this work by providing a summary of completed works, contributions of this dissertation, and future work.

2. BACKGROUND

2.1 Emotions

Emotions are important for the existence of mankind and serve as a means of non-verbal communication. Emotions are often confused with the word ‘mood’, but if examined in detail, both words embark a very different meaning. On one hand, mood is a less specific and less intense emotional state, while, on the other hand, emotion implies a very specific emotional state (Gaudine & Thorne, 2001). Mood is generally specified as either ‘good’ or ‘bad’. Whereas, emotions can be classified into six basic categories: anger, disgust, fear, happiness, sadness, and surprise (Ekman, Levenson, & Friesen, 1983). Facial expressions, body gestures, speech, etc. convey a plethora of information regarding the feelings or emotions being experienced by an individual (Castellano, Kessous, & Caridakis, 2008). These modalities will be discussed in detail, in the next section. Further, there is no clear understanding on the order in which brain processes occur after a particular event (Gross & Barrett, 2011) and that is why there are different theories behind emotion experience and recognition. Some of the most commonly known theories are James-Lange theory and Cannon-Bard theory (Dalglish, Dunn, & Mobbs, 2009).

2.2 Affective Computing

Affective computing is that branch of computing which deals with the study of emotions (Picard, 2000). The study of human emotions which includes identifying, construing, and simulating them, constitutes the core concept behind affective computing. The human ability to make decisions is governed by emotional aspects. Affective

computing deals with developing machines or computers, which are not only able to recognize, interpret, and process emotions, but are also able to make decisions according to the situation. This means that for a computer to be naturally and truly intelligent, understanding emotions is a must. Various applications of affective computing such as robotics, advertising, and healthcare applications are based on the same principle. The idea behind applying affective computing in the case of virtual friends, caring for paralytic patients, or people who have some sort of disability, is not only to assess the emotional state of the person involved, but also to get as close to reality as possible.

In our day-to-day life, we take cues from information corresponding to facial features, body posture, gestures, speech, physical state, etc., and try to perceive the emotion being experienced by others. In similar ways, we can make use of technology and use devices or sensors to capture the same information for emotion recognition through machines. For example, facial features, gestures, etc. could be captured by using a camera, and speech by microphone. Figure 2-1 shows the different characteristics or modalities which can be used to understand emotions.

The monitoring of physiological parameters, such as heart rate, body temperature, muscle activity, etc. can provide information related to the affective state of an individual. For example, when a person is happy, heart rate would increase, but there may be no change in body temperature. Also, a high heart rate can suggest that a person is either angry or nervous about something. Hence, we can say that, although, monitoring physiological parameters is a less obvious way of assessing human emotions, in comparison to facial features, speech, or body gestures, it plays an important role in affective computing. These parameters are particularly useful in knowing the

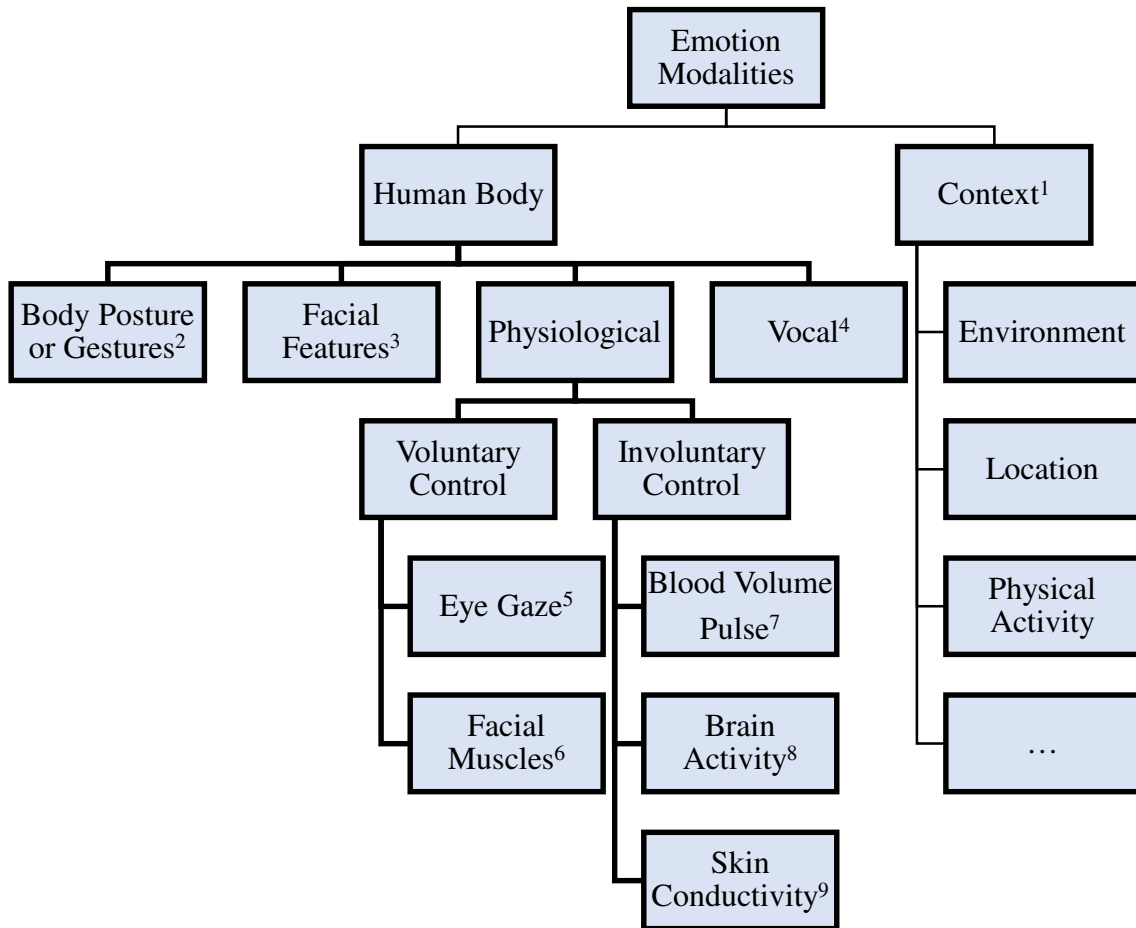


Figure 2-1: Different Emotion Modalities

¹ (Abowd, Dey, Orr, & Brotherton, 1998; Picard, 1997)

² (Chen, Tian, Liu, & Metaxas, 2012; Coulson, 2004; Gunes & Piccardi, 2007; Shan, Gong, & McOwan, 2007; Wallbott, 1998)

³ (Littlewort, Bartlett, Fasel, Susskind, & Movellan, 2006; Pantic & Rothkrantz, 2000)

⁴ (Morton & Trehub, 2001; Mozziconacci & Hermes, 1999; Nogueiras, Moreno, Bonafonte, & Mariño, 2001; Polzin & Waibel, 1998; Sobin & Alpert, 1999)

⁵ (Adams & Kleck, 2003; Bayliss, Frischen, Fenske, & Tipper, 2007; Wicker, Perrett, Baron-Cohen, & Decety, 2003)

⁶ (Broek, Schut, Westerink, Herk, & Tuinenbreijer, 2006; Dimberg, 1990; Hess, Kappas, McHugo, Kleck, & Lanzetta, 1989; Larsen, Norris, & Cacioppo, 2003; Sato, Fujimura, & Suzuki, 2008; Vehkaoja et al., 2005)

⁷ (Anttonen & Surakka, 2005; Lee & Yoo, 2008; M. Poh, Kim, Goessling, Swenson, & Picard, 2010; M. - Poh, McDuff, & Picard, 2011)

⁸ (Brown et al., 2010; Matthews et al., 2007; Murugappan, Rizon, Nagarajan, & Yaacob, 2010)

⁹ (Ming-Zher Poh, Swenson, & Picard, 2010; Nasoz, Alvarez, Lisetti, & Finkelstein, 2003)

emotional state of infants, elderly people, severely sick people or any of those who have difficulty communicating because of their age or any other physical or mental incapability.

The study of physiological monitoring can be broadly studied by monitoring the signals produced by various body organs, such as the heart, brain, skin, muscles, etc. The assessment of human emotions through physiological parameters is difficult as compared to assessment via facial expressions, speech analysis, and body postures (Picard, 1997). This is because the latter are more obvious to the human eye, and in terms of using devices, can be easier to capture via video or audio devices like cameras, and microphones. Physiological monitoring, especially for involuntary actions, on the other hand, is done via external devices and sensors. Physiological monitoring may prove to be a useful tool in studying the emotions of people who are physically challenged or have problems in communicating, as in the case of individuals with ASD.

A great deal of research has been done in the field of physiological monitoring as understanding human emotion is a popular topic for different disciplines, such as psychology, sociology, psychotherapy, computer science, etc. Most of the researchers have conducted lab experiments to support their research wherein the subjects are asked to self-rate their state of mind and are meanwhile monitored via cameras, sensors, etc. (Picard, 2003). This kind of lab set-up usually turns out to be intrusive in nature and also devoid of a natural setting to the participant for the expression of emotions.

There are a number of physiological methods for monitoring emotions, for which definitions are presented next. *Blood Volume Pulse* (or BVP) is measured by a technique called photoplethysmography where the human body or an organ is exposed to infra-red

light (Vicente, Barreto, & Taberner, 1996). The amount of reflected light is measured and a graph of the resulting waveform is plotted. The graph obtained indicates the amount of blood flow through the extreme body parts. *Skin conductivity* is measured through Galvanic Skin Response (GSR). The skin conductivity varies with the moisture level of skin and increases when the person is experiencing fear or nervousness (Boucsein, 2012). GSR is also known by other names, such as electrodermal activity (EDA), and skin conductance level. It is very useful in polygraphs or lie detector tests because people who are not telling the truth tend to give physiological cues (Pflanzer, 2013). The electrical activity in the brain can be monitored by *Electroencephalography* (EEG) and thus, EEG helps study brain waves (Teplan, 2002). The human brain comprises of billions of neurons, which generate electrical impulses, measured using EEG. EEG proves to be very helpful in evaluating head injuries, tumors, sleep disorders, epilepsy, etc. (Teplan, 2002).

Facial Electromyography (Facial EMG) is an EMG technique used to measure muscle activity along the facial features. The contraction of muscles results in an electrical impulse, which is then measured by the electromyography (Merletti & Parker, 2004). This technique is primarily focused on two muscle groups called the *corrugator supercilii* and the *zygomaticus major muscle*. The *corrugator supercilii* muscle is responsible for controlling the action around the brow and hence is also called the ‘frowning’ muscle. This muscle helps produce a negative emotional expression. On the other hand, the *zygomaticus major* muscle is responsible for controlling the action around the corner of the lips, and is involved in production of the positive emotions, like happiness (Larsen et al., 2003).

Various research works support the statement that emotions can be recognized by using bio-signals (Haag, Goronzy, Schaich, & Williams, 2004), such as EMG, ECG, skin temperature, BVP, and respiration. The feeling of anger would normally increase heart rate as well as body temperature. One might start perspiring while feeling nervous, and that would result in increased galvanic skin response or skin conductivity (Ax, 1953).

Apart from the cues that one gets from the human body about emotions, sometimes contextual information can also play an important role in understanding emotions. This contextual information can be found from the users' environment, location, the way he/she interacts with surrounding objects, the kind of activity the person is engaged in, etc.

2.3 Multi-Modal Affect Detection

As an observer, when we try to understand another person's emotions, we take cues from several factors, such as facial expressions, words, actions, context, etc. A higher heart rate and higher skin temperature correspond to the expression of anger whereas higher heart rate and lower skin temperature correspond to the feeling of sadness or fear (Ekman et al., 1983). In a similar way, affect detection gains more accuracy if done using several modalities rather than just one. This assertion can also be concluded from the several studies listed in Table 2-1.

2.4 Autism Spectrum Disorder (ASD)

Autism Spectrum Disorder (ASD) is a developmental disorder characterized by abnormal functioning in social interaction, communication, and restricted or, repetitive

Author, Year	No. of Subjects	Modalities	No. of Emotions	Algorithm/Technique for Affect Recognition
(Adibuzzaman et al., 2013)	8	Facial Expression and Energy Expenditure	6	Naïve Bayes Fusion
(Busso et al., 2004)	1	Facial Expressions and Speech	4	Support Vector Machine (SVM)
(Caridakis et al., 2007)	10	Facial Expressions, Body Gestures and Speech	8	BayesNet Classification
(Chen et al., 2012)	4	Facial Expressions, Body Gestures	10	SVM
(De Silva & Ng, 2000)	2	Facial features and Speech	6	Hidden Markov Models (HMM)
(D'Mello & Graesser, 2010)	28	Conversational cues, Body Postures and Facial Expressions	4	Linear Discriminant Analyses
(Gunes & Piccardi, 2007)	4	Facial Expressions, Body Gestures	6	BayesNet Classification
(Hussain & Calvo, 2011)	16	Heart activity and Facial Expressions		KNN, SVM, Decision Tree Algorithms
(Picard, Vyzas, & Healey, 2001)	1	Facial EMG, Blood Volume Pressure, Skin Conductance and Respiration	8	k-NN Classifier
(Pour, Hussain, AlZoubi, D'Mello, & Calvo, 2010)	16	Heart Activity, Facial EMG and GSR	8	Self-report
(Scherer & Ellgring, 2007)	12	Facial Expressions, Voice, Body Movements	14	Discriminant Analysis
(Shan et al., 2007)	23	Facial Expressions, Body Gestures	7	SVM
(Yoshitomi, Kim, Kawano, & Kilazoe, 2000)	2	Voice, Facial Image and Thermal Image	5	Neural Networks and HMM
(Zeng et al., 2006)	2	Facial Expressions, Voice	2	Adaboost multi-stream HMM

Table 2-1: State-of-the-Art: Multi-modal Affect Detection

behavior (American Psychiatric Association, 2013). Genetic, prenatal, and environmental factors are the most common causes associated with ASD (Persico & Bourgeron, 2006).

There are no medical tests available for diagnosing ASD. Since it is a behavioral disorder, there are assessment tools available for the diagnosis, such as patient history, observation, and certain questionnaires.

People with ASD may struggle with communicating and expressing emotions. Not only that, they also may have trouble understanding the emotions of people around them (Silver & Oakes, 2001).

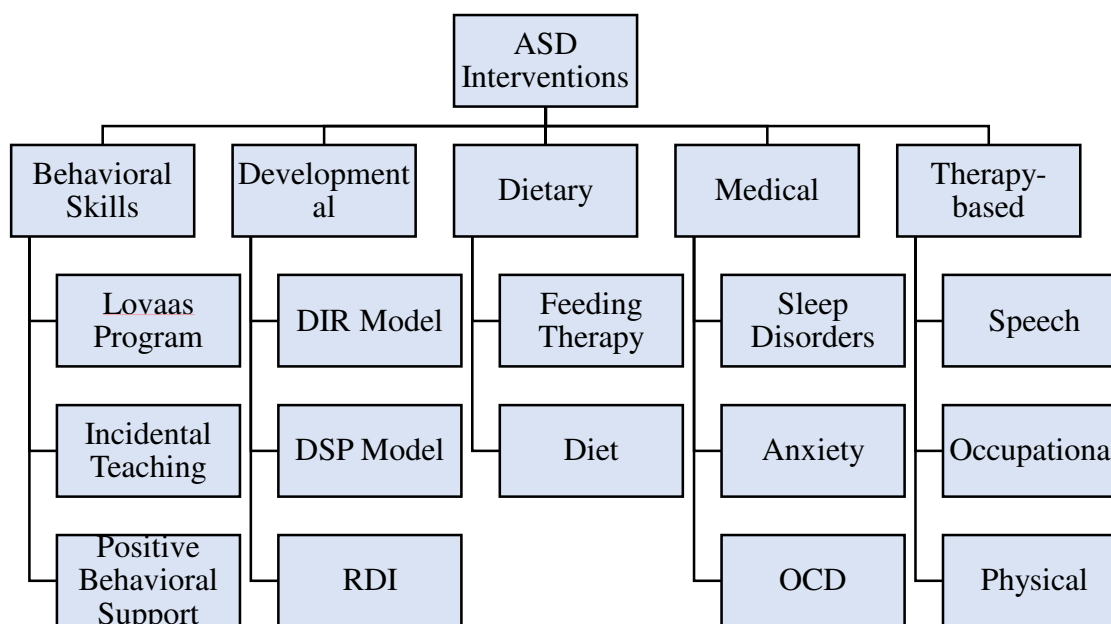


Figure 2-2: Classification of ASD Interventions

Abbreviations: ASD = Autism Spectrum Disorder, DIR = Developmental, Individual Difference, Relationship-Based Model, DSP = Developmental social-pragmatic Model, RDI = Relationship Development Intervention, OCD = Obsessive Compulsive Disorder

There is no particular cure for ASD, but a timely intervention can improve the overall development of the child. There is a wide variety of interventions and each one of those is targeted towards a specific problem. Depending on the child's needs, a combination of more than one intervention can be helpful. Some of the interventions involve parent or primary caregiver participation in addition to child participation. Figure 2-2 shows the classification of these interventions on the basis of focal points of different techniques (Francis, 2005; Green et al., 2006). Behavioral interventions focus on teaching and developing behavior and adaptive skills (Howlin, Magiati, & Charman, 2009). Developmental approaches are targeted towards forming and maintaining relationships. The literature shows that dietary interventions are helpful in reducing digestive problems, and sleep-related problems, and can also be helpful in providing a well-balanced diet to children with ASD (Neggers, 2011). Medical intervention might be required to improve secondary conditions like anxiety, obsessive compulsive disorders, and sleep disorders. Lastly, therapy-based interventions provide professional help in case of speech, adaptive/occupational domains, and physical activity/coordination related problems (Baranek, 2002).

One study shows that the prevalence rate of ASD has increased from 1 in 88 (in the year 2008) to 1 in 68 children (in the year 2010) (Developmental Disabilities Monitoring Network Surveillance Year 2010 Principal Investigators & Centers for Disease Control and Prevention (CDC), 2014). This increase in prevalence rate not only implies the increase in number of cases of ASD, but also implies that with more awareness and improvement in diagnostic tools over the years, the detection rate of ASD has also increased (Kim et al., 2011). The lifetime cost for caring for an individual with

autism ranges from \$1.5 million to \$2.5 million (Buescher, Cidav, Knapp, & Mandell, 2014). The United States economy is impacted with a cost of \$235 billion annually, which includes costs towards medical insurance, education, housing, transportation, employment, and research work (Buescher et al., 2014). ASD has its effect on the employment sector as well, because as per a study, 35 percent of working age individuals with ASD do not have paid jobs (Shattuck et al., 2012).

Given this basic knowledge about what is meant by ASD, its causes, and its impacts, this review can address the technology that can be used with this population. If affective computing can be utilized with people with ASD, communication of their affective state could be improved. It may also in turn help improve the social competence of people with ASD. Children with ASD are recommended to undergo therapy for 25 hours per week or more (Foxx, 2008). The development of therapeutic tools can make treatments more accessible in terms of cost, time, and effort (Heron & Smyth, 2010). The following three studies presented here will attempt to address these issues.

3. PHYSIOLOGICAL MONITORING OF ADOLESCENTS WITH ASD TO STUDY AROUSAL DURING PEERS INTERVENTION

3.1 Motivation

Variability in the level of functioning of individuals with ASD (American Psychiatric Association, 2013) makes diagnosis, treatments, and interventions challenging. In addition, anxiety or anxiety disorders are considered to be one of the most common comorbid disorders in individuals with ASD (van Steensel, Bögels, & Perrin, 2011; White et al., 2009; White et al., 2010). Several studies suggest that individuals with ASD, vs. typically developing children, are at an increased risk of anxiety disorders (J. A. Kim, Szatmari, Bryson, Streiner, & Wilson, 2000; Kuusikko et al., 2008; Leyfer et al., 2006; Mayes, Calhoun, Murray, Ahuja, & Smith, 2011). Anxiety in children with ASD may lead to more complex behaviors like aggressive and oppositional behavior (J. A. Kim et al., 2000), impairment in social functioning (de Bruin, Ferdinand, Meester, de Nijs, & Verheij, 2007), and increased negative thoughts (Farrugia & Hudson, 2006). If these behavioral problems are not treated in time, they can become persistent and may be difficult to treat. The assessment of anxiety disorders in individuals with ASD is difficult, because of the overlapping of symptoms between anxiety and ASD, inherent communication difficulty in ASD, and idiosyncratic nature of this disorder (Davis, Saeed, & Antonacci, 2008; White et al., 2009).

Anxiety is said to have cognitive and somatic components (Liebert & Morris, 1967). Cognitive or mental components are associated with negative expectations and consequently poor performance, whereas somatic components are associated with the

arousal of autonomic nervous system (ANS) or physiological arousal (Vickers & Williams, 2007; Vitasari et al., 2011). This physiological arousal is usually experienced by increase in heart rate, shortness of breath, and sweating of palms. Skin conductance response (SCR) or electrodermal activity (EDA) serves as a good measure of arousal from the sympathetic nervous system (SNS), which may be helpful in understanding the emotional response of an individual, especially in those that are less verbally capable.

Understanding anxiety and its interaction with emotion comprehension and expression in ASD is a growing and multifaceted area of research. On one hand, several physiological signs, such as heart rate, EDA, muscle activity, etc. provide information related to the affective state of an individual. On the other hand, there are behavioral ways of expressing emotions such as through facial expressions, body gestures, and speech (words and tone).

Author, Year	N	Age Range (years)	SCR or EDA Stimuli	Results (ASD Group compared to Control Group)
(Blair, 1999)	20	M: 12	Slides with distress cues, threatening and neutral stimuli	No difference
(Cohen, Masyn, Mastergeorge, & Hessel, 2013)	29	10-17	Visual Stimuli using pictures	Higher SCR in ASD Group
(Hirstein, Iversen, & Ramachandran, 2001)	37	3-13	Looking at a person vs. object	ASD Group: No change in SCR Control Group: Higher SCR to the person than object
(Hubert, Wicker, Monfardini, & Deruelle, 2009)	16	M: 25;6	Videos with facial stimuli	Lower SCR in ASD Group

(Joseph, Ehrman, McNally, & Keehn, 2008)	20	9-16	Face images with direct and averted gaze	Higher SCR in ASD Group
(Kushki et al., 2013)	12	8-15	Neutral Movie and Stroop task	ASD Group: Neutral Movie - Elevated SCR, Stroop Task - Blunted SCR
(Kylliäinen & Hietanen, 2006)	12	9-12	Face images with direct and averted gaze	Higher SCR in ASD Group
(Levine et al., 2012)	19	8-12	Trier Social Stress Test (TSST)	No difference
(Louwerse et al., 2013)	31	12-19	Face images with direct and averted gaze	No difference
(Mathersul, McDonald, & Rushby, 2013)	30	18-73	Happy, Angry and Neutral faces	Lower SCR for pleasant images
(Riby, Whittle, & Doherty-Sneddon, 2012)	12	12-18	Happy, Sad and Neutral faces	No difference
(Shalom et al., 2006)	10	9-18	Pleasant, Neutral and Unpleasant Images	No difference
(South, Dana, White, & Crowley, 2011)	40	8-18	Balloon Analogue Risk Task (BART)	No difference
(van Engeland, Roelofs, Verbaten, & Slangen, 1991)	20	M: 9;7	Visual Stimuli using fixation task	Lower SCR in ASD Group
N indicates size of ASD sample and M indicates Mean Age (Years; Months)				

Table 3-1: Studies of Skin Conductance Responses in Individuals with ASD

Abbreviations: ASD = Autism Spectrum Disorder, SCR = Skin Conductance Response, EDA = Electrodermal Activity

There are different approaches for studying physiological arousal and consequent emotion processes. One review study (White et al., 2014) provides a comprehensive study of these approaches and list startle responses, skin conductance response, and cardiac activity as some of the most common approaches in understanding emotion in

ASD. The focus of the current study involves skin conductance, or EDA, as an arousal measure in individuals with ASD. Though there has been considerable work done in this area (see Table 3-1), the results of these studies are not consistent and hence do not provide a clear understanding of the role played by EDA in emotion regulation of individuals with ASD. One reason for this inconsistency is that the stimuli used to measure EDA data in the majority of these studies (12 out of 14) is that of emotion eliciting pictures, while in the remaining two the stimulus is a stress task. These stress tasks are a set of validated procedures that are known to induce stress in the participants. Moreover, all of these studies compare the EDA levels of individuals with ASD to that of typically developing (TD) control group. No study, to date, has examined EDA data as a base to understand the emotions experienced by children with ASD in their day-to-day life or over time, in a longitudinal fashion. Both of these types of investigations are needed, as laboratory studies of EDA in ASD in response to stimuli may not provide an adequate conceptualization of the day-to-day functioning of the individual. More specifically, an unfamiliar, one-time laboratory measurement of EDA may already be confounded by the fear or anxiety that novel situations elicit in individuals with ASD (Gillott, Furniss, & Walter, 2001).

Facial expressions have long been studied as a means of understanding emotions. The automated analysis of facial expressions is an intricate process and can be further broken down into ordered steps for easier understanding as follows: (1) detection of the face, (2) extraction of facial features, and (3) classification of facial expressions (Pantic & Rothkrantz, 2000). The Facial Action Coding System (FACS) (Ekman & Friesen, 1978) is the most common technique to study facial expressions, but FACS has its own

set of limitations irrespective of the classification method used, manual or automated (Pantic & Rothkrantz, 2000). Combinations of several techniques (Parameterized Appearance Modeling (De la Torre & Cohn, 2011), Eigenfaces (Turk & Pentland, 1991), Principal Component Analysis (Hotelling, 1933), classification methods (Pantic & Rothkrantz, 2000), clustering (Jain & Dubes, 1988), etc.) may be employed for a more effective analysis of facial expressions (De la Torre & Cohn, 2011; Pantic & Rothkrantz, 2000).

As in the case of SCR studies, the studies pertaining to emotion perception and production of facial expressions by individuals with ASD fail to provide a consensus (Kennedy & Adolphs, 2012). Some studies suggest that individuals with ASD do not perform as well as a TD control group in labeling basic emotions, whereas others report that there is no such difference in the perception of the two groups (Tanaka et al., 2012). There are two approaches for emotion based studies. One approach is examining the emotion perception or understanding of individuals with ASD. A second approach concerns examining facial emotion production of individuals with ASD, and how these displays are perceived by others around them, which conveys information about their expressiveness of emotion. Although there have been many studies on the understanding of emotion in individuals with ASD (Harms, Martin, & Wallace, 2010), there have been comparatively few studies on the identification or interpretation of emotional expressions produced by individuals with ASD.

Picard, Vyzas, and Healey (Picard et al., 2001) have listed five important design-factors to be considered for a study that requires elicitation of emotions. These considerations are as follows: *event-elicited vs. subject-elicited stimulus, real-world vs.*

lab setting, emphasis on internal feeling vs. external emotion, hidden-recording vs. open recording, and other vs. emotion purpose behind the study. These factors, if addressed, can provide a naturalistic environment for the study of emotions.

The Present Study

The primary objective of this study was to investigate the presence, expression, and self-understanding of physiological arousal in adolescents with ASD while attending an empirically validated social skills intervention program, PEERS – Program for the Education and Enrichment of Relation Skills (Laugeson & Frankel, 2011). The physiological arousal was measured via a wireless wristband, a Q-Sensor (Q-sensor: Affectiva, Inc.), worn at every intervention session, in order to unobtrusively collect EDA data. Individual subjects' facial expressions during intervention sessions were captured via a video camera, which were then analyzed using machine learning algorithms to identify if the emotions were expressed on the face. Participants also rated their anxiety on a brief questionnaire, the State-Trait Anxiety Inventory (STAI) (Marteau & Bekker, 1992) before and after each intervention session to assess the self-awareness of their emotional state. These three facets allowed the study to examine the relationship between the “Have-it” (EDA physiological arousal), “Show-it” (facial expressions), and “Know-it” (self-rated report of emotion) categories of anxiety and arousal. The primary reason for the adolescent participants to be in the experimental sessions was to attend PEERS, and the emotion aims of the study were secondary to the PEERS intervention. This setting provided a natural environment for data collection.

3.2 Methods

3.2.1 Participants

Initially, 13 male adolescent participants were recruited for this study over the span of one and half years. Since this study was an additional part to the PEERS intervention, the inclusion criteria was as specified by the PEERS research group (Van Hecke et al., 2013). Briefly, participants were required to score at or above a combined IQ score of 70 on the Kaufman Brief Intelligence Test (Kaufman & Kaufman, 2005), and at or above autism spectrum categorization on the Autism Diagnostic Observation Schedule, Module 4, Generic (Lord, Rutter, DiLavore, & Risi, 1999). In addition, the consent and/or assent of the participants were obtained separately for this part of the study. Participants were reminded that they could withdraw from the emotion-related tasks of the current study at any time, without affecting their participation in PEERS. Participants were not compensated for emotion-related tasks, but the PEERS intervention was provided at no charge. It was noticed that one participant, S011, sat with his head down for the entire session of PEERS, hence his facial video data was unable to be analyzed for facial expressions. The subject was thus dropped from the study, leaving 12 male participants. The characteristics for the participants are summarized in Table 3-2.

3.2.2 Stimuli

The study aimed to have a naturalistic environment for studying anxiety or physiological arousal among adolescents with ASD, and PEERS sessions provided that.

SN	Age (at intake)	Gender	Race	Ethnicity	IQ Score	Parents income	Parent1 Education	Parent 2 Education
S001	12	M	White	Not Hispanic	136	75K-100K	Master's	PhD/M D/JD
S002	12	M	White	Not Hispanic	104	50K-75K	BA	Some College
S003	13	M	Asian	Not Hispanic	130	100K plus	PhD/M D/JD	PhD/M D/JD
S004	15	M	White	Not Hispanic	74	75K-100K	Some College	Jr. College Deg
S005	12	M	Asian	Not Hispanic	116	100K plus	Master's	Master's
S006	12	M	White	Hispanic	138	50K-75K	Master's	Some College
S007	14	M	White	Not Hispanic	116	100K plus	Some College	High School
S008	16	M	White	Not Hispanic	102	50K-75K	Master's	Voc/Tech
S009	16	M	White	Not Hispanic	103	100K plus	Some College	Voc/Tech
S010	18	M	White	Not Hispanic	100	25K-50K	Jr. College Deg	High School
S012	12	M	White	Not Hispanic	111	100K plus	BA	BA
S013	12	M	White	Not Hispanic	94	100K plus	BA	Master's

Table 3-2: Participants' Characteristics for ASD Group

Abbreviations: M = Male, IQ = Full-scale Intellectual Quotient from Kaufman Brief Intelligence Test

It is a parent-assisted intervention, which specifically targets skills pertaining to making friends, having conversations, and handling teasing and disagreements (Laugeson et al., 2009). The intervention consists of 14-weekly sessions, where each session is about 90 minutes in length. There are separate (but concurrent) sessions for adolescents and parents. These groups are led by trained graduate students under the supervision of a certified PEERS-provider. Hence, PEERS was able to provide a naturalistic classroom-based setting. Although this program in itself has a strong evidence-base for use with teenagers with ASD (Laugeson et al., 2012), the uniqueness lies in using PEERS with the aim of understanding anxiety and arousal over time in ASD.

3.2.3 Measures

3.2.3.1 Physiological Measure of Arousal

Each participant was given a wristband called a Q-sensor, which is a wearable bio-sensor (Q-sensor: Affectiva, Inc.). The participants wore the Q-sensor on their wrist and the wristband collected continuous data pertaining to their EDA over the 1.5-hour session. EDA is a measure of sympathetic response and is measured in micro-siemens (μS). With the arousal of the sympathetic nervous system (fight/flight system), the sweating glands on the skin start producing sweat, which is followed by increase in EDA. The data collected for each participant was saved as a file, which could be reviewed using the accompanied software. The software allows conversion of the file data into excel format, which can further be used for mathematical data analysis.

3.2.3.2 Behavioral Measure of Arousal

The participants were recorded via two video cameras. One video camera was positioned so as to capture the facial expressions of the participants. The second video camera captured the events happening in the room, so as to measure contextual information. Just like the EDA data, video data from the cameras were also recorded for all 14 sessions of the intervention. The video and EDA data were time-linked, so that the EDA events could be associated with specific points in time on the video.

3.2.3.3 Cognitive Measure of Anxiety

Participants completed a six-item short form of the Spielberg State-Trait Anxiety Inventory (STAI) (Marteau & Bekker, 1992) at the start and end of each session of PEERS intervention. This six-item form is a self-rating scale and has been validated for providing similar scores to those obtained using the full 20-item STAI. It has satisfactory reliability and is useful in cases of time constraint (Marteau & Bekker, 1992). Cronbach's alpha reliability was found to be 0.78 (from the data collected for this study) for the total anxiety score. The six-items include both anxiety-present (e.g. 'I am tense') and anxiety-absent (e.g. 'I am relaxed') items, and are rated on a four-point Likert-type scale.

3.2.4 Procedure

3.2.4.1 EDA Data Analysis

The EDA data analysis consisted of calculating several related parameters: maximum EDA, minimum EDA, mean EDA, area under the curve, standard deviation, and peaks per minute. These parameters were tabulated for each session and for each

participant. Out of all these parameters, maximum EDA was most useful in building the image database (see ‘Preparing the Image Database’). Other parameters were used in the regression analysis, which will be discussed later in this paper.

3.2.4.2 Preparing the Image Database

The EDA Analysis provided a crucial parameter for building the image database. For each participant, the time corresponding to the maximum EDA value in each session was calculated. Then, the facial image of the participant at that particular time in the video recording was captured (see Figure 3-1). It is to be noted that the images shown here have been intentionally turned into low resolution images to maintain participant anonymity. This image was labeled as the HiEDA image. If more than one instance was found for maximum EDA, preference was given to the instance with a better facial

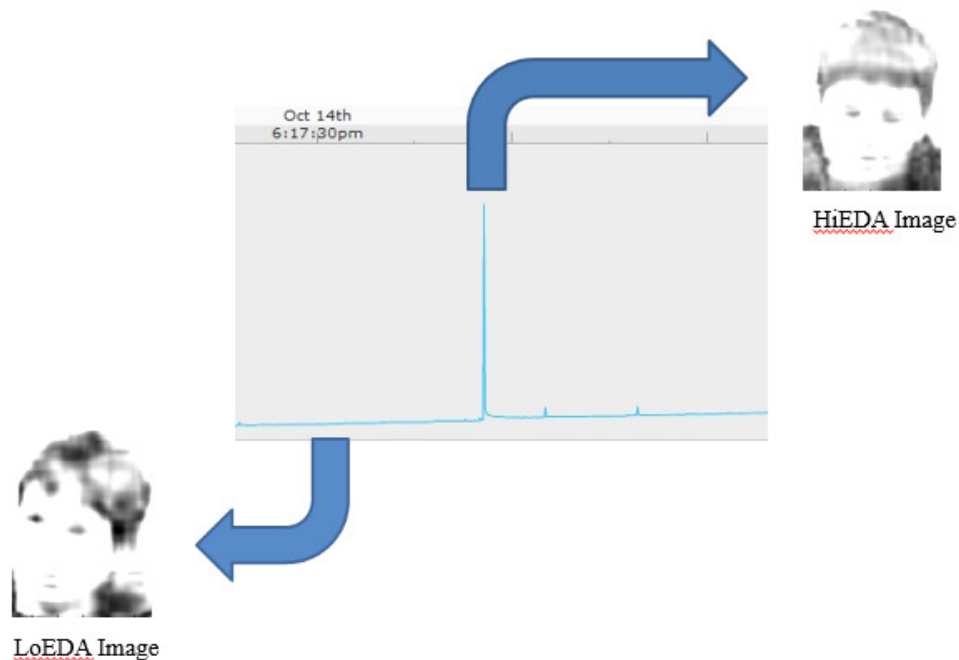


Figure 3-1: Preparing the Image Database using EDA Data

image, in terms of clarity. Similarly, a period of relatively low EDA was chosen and a corresponding image was captured and labeled as the LoEDA image.

This process was completed for all the 12 participants, for a total of 126 HiEDA and 126 LoEDA images. Table 3-3 shows the number of images in the image database for each participant (from the ASD group).

SN	No. of Images	Comments (if any)
S001	12	Dropped from PEERS after Session #6
S002	12	Recruited for this study after S001 dropped
S003	16	
S004	24	
S005	26	
S006	28	
S007	12	Dropped from PEERS after Session #6
S008	28	
S009	26	
S010	12	Dropped from PEERS after Session #7
S011	--	Excluded from this study because of bad data
S012	28	
S013	28	

Table 3-3: Composition of Image Database

3.2.4.3 Feature Extraction

The Eigenface method (Turk & Pentland, 1991) was used for feature extraction from each image in the image database. This method is based on Principal Component Analysis (PCA) and can be used to generate eigenfaces (a set of eigenvectors). Each face or picture in the database was written as a linear combination of these eigenfaces (see Figure 3-2). The weights (w_1, w_2, w_3, \dots) described the contribution of each eigenface to a

particular image. The classification methods were then applied on these weights for further understanding of facial images.

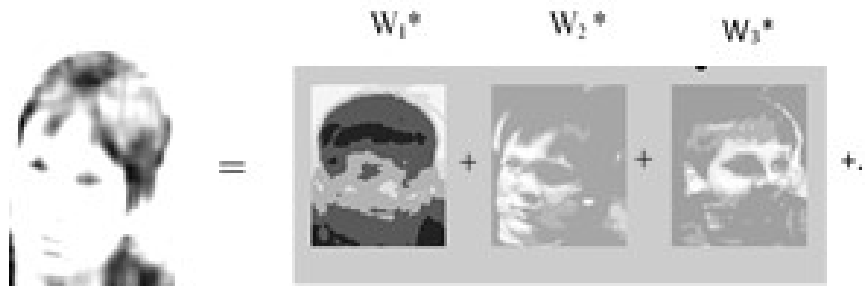


Figure 3-2: Facial Image as a Linear Combination of EigenFaces

3.2.4.4 Image Clustering

k-means clustering (MacQueen, 1967) was applied on the image database to partition image data into groups. k-means clustering is a simple and widely used clustering technique, where k is the number of desired clusters. The value of k was set to the number of participants to check whether the images from the same participants were clustered together or not. A different value of k was selected to check if the images were clustered according to the arousal level (high or low EDA images).

3.2.4.5 Image Classification

Image classification was done by employing supervised learning, wherein a labeled training dataset is used to classify the test dataset. The image database was divided into two sets – training and test data sets. The training data set, as the name suggests, was used to train the algorithm while the test data set was used to test the algorithm. The division between training and test data sets was based on different approaches and will be explained later in the results section. The algorithms used for

classifying images into HiEDA image or LoEDA image were: k-Nearest Neighbor algorithm and Support Vector Machines.

i) k-Nearest Neighbor (kNN) Algorithm

kNN is one of the simplest classification techniques in machine learning (Altman, 1992). Each of the samples in the training data has a class label. An unlabeled sample from the test data is assigned the class by the majority of class votes from k nearest neighbors. In our case, k was chosen to be 1, 3, or 5, i.e. the unlabeled sample was assigned to the class of majority of its nearest neighbors from training samples. The distance metrics used for finding the nearest neighbors were 'euclidean distance' and 'cosine distance'.

ii) Support Vector Machines (SVM)

SVM is one of the best techniques for binary classifications (Cortes & Vapnik, 1995). In our case, the data had to be classified into two classes (HiEDA or LoEDA images), hence SVM technique was a very appropriate choice. In SVM, the samples in training data are divided into two classes by a hyperplane. Different functions for this hyperplane were used- linear, quadratic, polynomial and Gaussian radial basis function (rbf).

3.2.4.6 Regression Analysis

A multiple regression analysis was performed to predict average STAI anxiety score (dependent variable) of an individual during each session from EDA parameters such as, mean EDA, max EDA, min EDA, area under curve, peaks per minute (ppm), and mean temperature.

3.2.5 Results

3.2.5.1 EDA Data Analysis

Different EDA-based parameters (maximum EDA, minimum EDA, mean EDA, area under the curve, standard deviation, and peaks per minute) were observed for each subject during each session of intervention. A wide variability was seen across the participants; as such, it could be that the content of each intervention session impacted the EDA of each participant differently. Maximum EDA for all 12 participants ranged from 0.014 to 11.37 μS (Mean = 1.962 μS , Std. Deviation = 2.398).

3.2.5.2 Image Clustering

The k-means clustering technique was used for un-supervised learning of the image dataset. For experimental purposes, different values of k were tried, but the most logical ones with respect to the database of the study were $k=2$ and 12 . This logic was based on the expectation that the image database could be clustered according to HiEDA and LoEDA images or it could be clustered according to the different faces in the database, i.e., the number of participants. In this study, the clustering algorithm did not find any particular grouping among the images. Figure 3-3 and 3-4 shows the plots of k-means clustering results (for $k=12$ and $k=2$). As can be seen from the figure 3-3, each cluster has images belonging to several users. Similar results were observed for two clusters, i.e., $k=2$ (figure 3-4). This suggests that the variation in the images made recognition difficult for the machine learning algorithms.

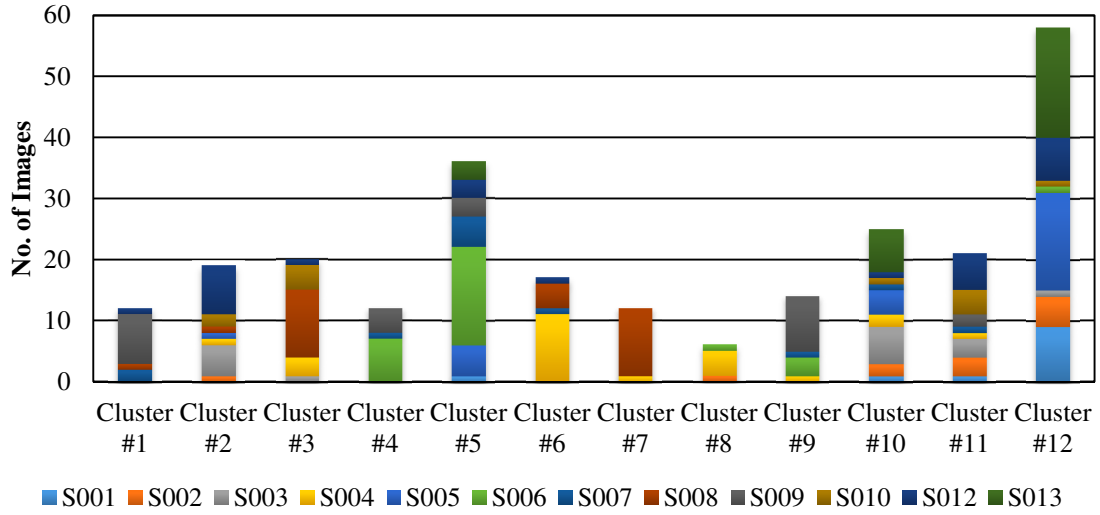


Figure 3-3: Number of Images in Each Cluster (for $k=12$), using k-Means Clustering Technique

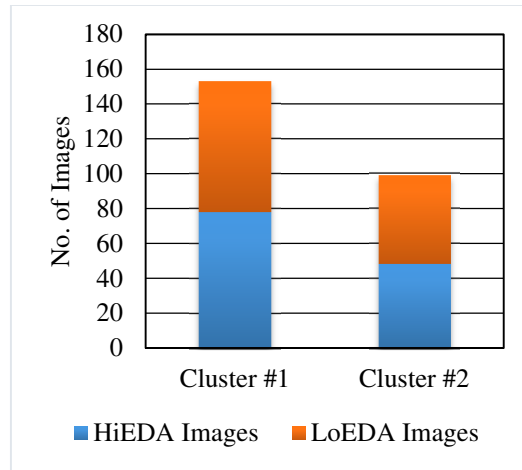


Figure 3-4: Number of Images in Each Cluster (for $k=2$), using k-Means Clustering Technique

3.2.5.3 Image Classification

The image classification was done for all the 12 participants. Three different approaches were used for obtaining different sets of ‘Training’ and ‘Test’ data sets. The details of these approaches are as listed below:

Approach 1 - Cross-Validation

This approach was applied on each subject individually. The images of a subject were divided into the number of sessions attended by that subject. For example, S001 attended six sessions of the intervention. As per the construction of image database, there were two images (one HiEDA image and one LoEDA image) from each session. So, for S001 there were six pairs of images. At a given time, one pair of images was used as the test image and the remaining five pairs as training images. The process was repeated until

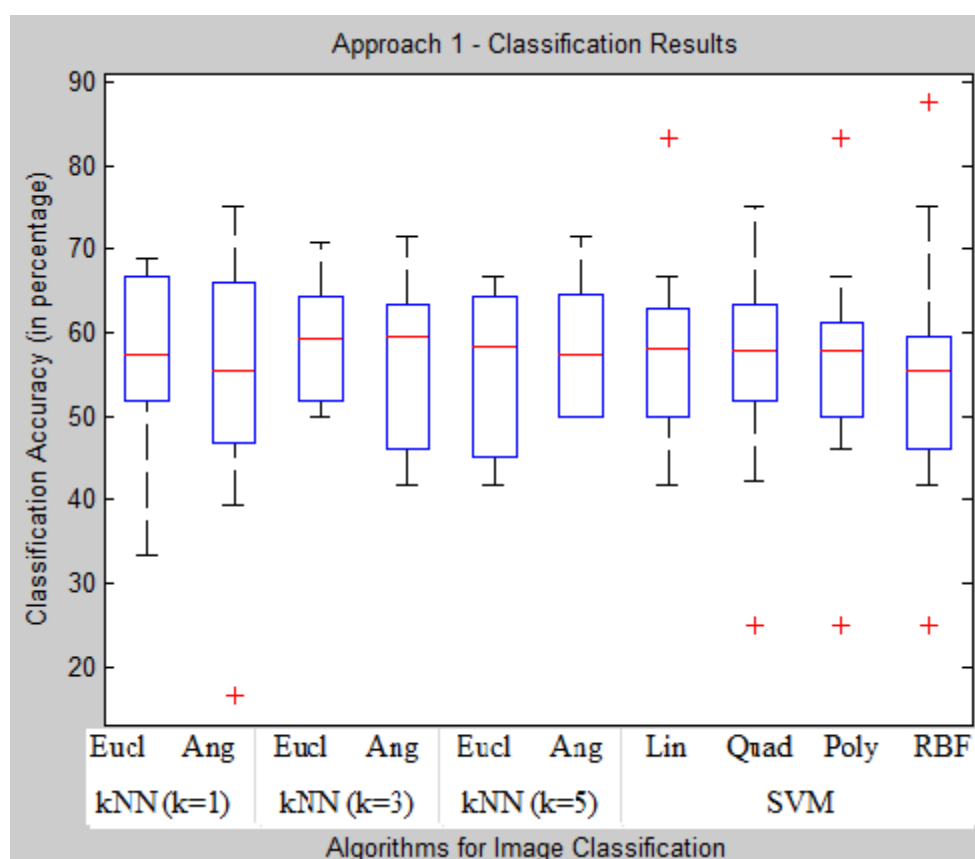


Figure 3-5: Approach 1 – Cross Validation: Classification Accuracies Obtained using kNN and SVM with Different Parameters (varying ‘ k ’ and distance metrics)
 Abbreviations: Eucl = Euclidean, Ang = Angular, Lin = Linear, Quad = Quadratic, Poly = Polynomial, and RBF = Radian Basis Function

each pair was used as the test image. The average accuracy of classification was then calculated for the subject. The same approach was carried out on other subjects in the study. The classification results obtained from all 12 subjects are shown in Figure 3-5.

Approach 2 - Leave One Subject Out

This approach was applied on the entire image database. The image database was comprised of images from 12 subjects. For this approach, images of one subject (say, S001) were used as test images and images of all the remaining subjects (S002 to S013, S001) were used as test images and images of all the remaining subjects (S002 to S013,

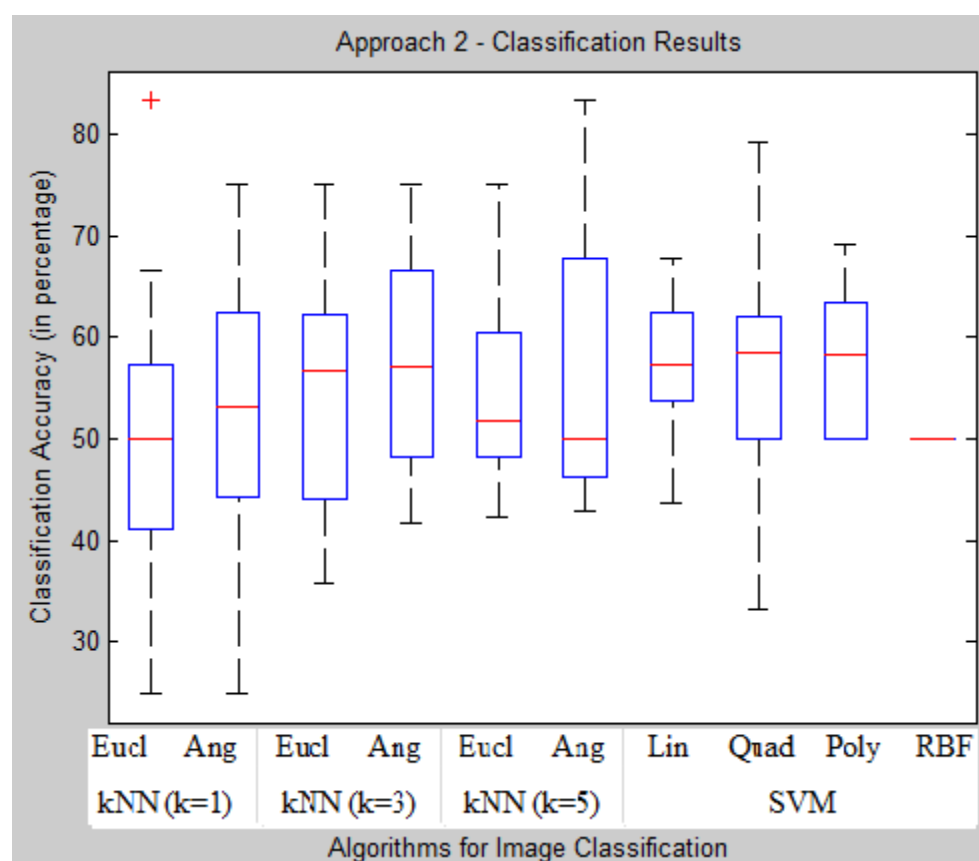


Figure 3-6: Approach 2 – Leave One Subject Out: Classification Accuracies Obtained using kNN and SVM with Different Parameters (varying ‘ k ’ and distance metrics)

Abbreviations: Eucl = Euclidean, Ang = Angular, Lin = Linear, Quad = Quadratic, Poly = Polynomial, and RBF = Radian Basis Function

except S011) were used as training images. The process was repeated until each subject's image set was used as the test image. The average accuracy of classification was then calculated (see Figure 3-6).

Approach 3 – Bootstrapping

Bootstrapping is a resampling technique which allows us to infer about a population from a relatively small sample (Efron & Tibshirani, 1994). In this approach, 80% of the samples or images (without replacement) were picked in a random way, these samples were then classified one by one, and 100 such iterations were run. The classification accuracy was then found to be in the range of 40-59%.

3.2.5.4 Regression Analysis

Multiple regression analysis indicated a significant relationship between maximum EDA during each PEERS session and the average score for self-reported STAI anxiety, $F(9,123) = 1.3, p < 0.05$. This significant relationship between the variables suggested that the participants of this study were self-aware of their arousal states.

3.3 Discussion

The first goal of this study was to identify the situations which cause physiological arousal among adolescents with ASD. The EDA data collected using the Q-sensor wristband was helpful in identifying the periods of maximum and minimum arousal during each session of intervention. The second goal of this study was to see if this arousal is evident from facial expressions of adolescents with ASD. Different machine learning algorithms (kNN and SVM with different parameters) were employed to classify the facial image data. These algorithms were able to predict the EDA arousal

states (high and low) with only slightly better than chance accuracy, 56.3%. The clustering technique using k-means was not able to clearly cluster the image data according to arousal states or participants. This result led to the conclusion that the linkage between facial expressions of adolescents with ASD and their physiology is weak. When the change in different facial expressions is close to non-existent, the machine learning algorithms were not able to spot the difference in high and low arousal states with clarity. This situation could be the reason behind the low classification accuracy of image dataset. The third goal of this study was to see if the adolescents were self-aware of their anxiety. For this goal, a regression analysis between the maximum EDA and average anxiety score showed a significant relationship ($F(9,123) = 1.3, p < 0.05$). The overall results of this study led to the conclusion that there are instances when physiological arousal is experienced by the participants (“Have-it”), which they do not necessarily express through their facial expressions (don’t “Show-it”), but are self-aware of the arousal (“Know-it”).

One of the limitations of this study was its small sample size. The design of this study is such that with more participants comes the need of more wristbands and video cameras. This requirement poses financial as well as practical constraints on the experimental setting. However, in order to have more participants included in this study, the recruitment will be continued during future PEERS sessions. Another limitation was the lack of comparison with a group of typically developing adolescents. The challenging part here will be to create the same environment for stimuli for a control group as for the experimental group. Future studies will attempt to address this limitation.

In the next chapter, the results of machine learning algorithms are compared to

that of human assessment of emotions. Undergraduate students were recruited, who then rated the images (from the image database) on their arousal level (high or low). This resulted to a direct comparison between the interpretation of emotions from facial expressions by a machine (or computer) and a human. This study was devised to address the question of whether the machine learning algorithms were poor at classifying emotional faces, but perhaps human perception might be better at such a task. The study and its results are discussed in detail in Chapter 4.

As a part of future work, the research will examine the individual EDA trajectories of these participants on the basis of treatment outcomes. Our long-term goal is to build a home-based monitoring tool for studying emotions in individuals with ASD.

There is a very limited literature to study the physiology of adolescents with ASD, especially in connection with expression of facial displays of emotion. This study provides an early look at the relationship between “have-it”, “know-it”, and “show-it” components of physiological arousal and emotion among adolescents with ASD. With a larger dataset and inclusion of a comparison group, this study can provide better understanding of emotions in ASD and can also pave the way for future research in this area, such as treatment outcomes.

4. UNDERSTANDING AROUSAL FROM FACIAL IMAGES OF ADOLESCENTS WITH ASD – A SUBJECT POOL STUDY

4.1 Motivation

This study was an extension of the work described in the previous chapter. In the last chapter, it was discussed, how the facial images of the adolescents with ASD were classified into high and low arousal images by machine learning algorithms. The average accuracy obtained in that case was just a little better than chance level. Thus, this study explored whether humans are better at this kind of assessment about arousal as compared to machines (or computers).

4.2 Methods

4.2.1 Participants

An IRB approved, psychology subject pool study was conducted where 43 participants, aged 18 years and above, were recruited. All the participants were undergraduate students at Marquette University. They were consented for their participation in the study. They received credit in psychology courses as compensation for their participation in the study. The participants' characteristics are shown in Table 4-1.

The adolescents with ASD, whose images were to be shown to these undergraduate participants, were re-consented for this part of the study. They, as well as their parents, were informed of the study and were asked if they agreed to allow their facial images to be shown to the undergraduate participants of this study. Two out of 12

participants (from ASD group) did not consent for this study, hence their images were not included in the study. This reduced the image database from 252 images to 228 images.

Characteristic	
Age M(SD), years	19.1 (0.9)
Gender (percentage)	
Male	27.9
Female	72.1
Race (percentage)	
Asian	7.0
Black/African American	2.3
White/Caucasian	81.4
Hispanic (any race)	7.0
Native American	0.0
Other	2.3
Current School Year (percentage)	
Freshman	58.1
Sophomore	25.6
Junior	16.3
Senior	0.0
Family Income (percentage)	
Under 50K	18.6
50-75K	14.0
75-100K	23.2
100K plus	44.2

Table 4-1: Participants' Characteristics for Undergraduate Group

4.2.2 Stimuli

Preparation of the image database has already been discussed in Section 3.2.4.2. The image database was updated by removing images of participants (from ASD group) who did not consent for this study. The images from the updated image database (HiEDA and LoEDA images, in a randomized order) were shown to the undergraduate group of participants.

4.2.3 Measures

To see if humans were better at understanding the arousal of a person from his/her facial expressions, an online questionnaire was developed for participants using Google Forms. This online questionnaire consisted of 5 items for participants' demographic information followed by the instructions related to the study. The participants were then directed to the pages containing images from the image database. A sample survey is shown in Appendix A. These images were to be rated on high/low arousal and positive/negative valence. Although data about 'valence' information of the facial image were collected too, this data was not analyzed in our study.

4.2.4 Procedure

Data for this study were collected over four 1-hour sessions, where 10-12 participants completed a session. These sessions were conducted in a computer lab, so as to accommodate several participants in each session. The participants were consented on their arrival and were given a unique participant code to be entered on the online survey. Each participant was seated in a chair with a web-enabled desktop in front of them for taking the online survey. A PowerPoint slide containing a brief explanation and examples of high/low arousal and positive/negative valence was projected on the screen (see Appendix B) for the entire duration of each session, such that it was easily visible to all the participants and could be referred to in case of need.

4.2.5 Results

228 images in the image database were rated on high/low arousal level by 43 participants of this study. The reliability of agreement between 43 raters when assigning a

category to these 228 images was assessed using Fleiss' kappa coefficient (Fleiss, 1971). It was found to be 0.23 on a scale of -1 to 1, indicating a fair level of agreement between the raters. The average classification accuracy for the image database was found to be 51.08%, ranging from 44.3% to 57.89%.

4.3 Discussion

The goal of this study was to compare the machine algorithms' accuracy to human accuracy in identifying arousal from facial images of adolescents with ASD. A comparison of the average accuracies of classification obtained from machine learning algorithms (56.3%) and humans (51.1%) led us to the conclusion that in present setting of the experiment, humans weren't any better at predicting the arousal level from the facial expressions. Again, this finding could be because of the lack of change in facial expression from one arousal state to another (high to low, or vice-versa) of adolescents with ASD. Moreover, the inter-rater reliability, found using Fleiss' kappa coefficient, indicated only a fair level of agreement between the undergraduate participants. This finding indicated that the participants were not consistent among themselves in rating an image as high or low arousal.

One of the limitations of this study is the lack of contextual information while rating the facial images on arousal level. The literature shows that context plays an important role in everyday emotional experiences (Hassin, Aviezer, & Bentin, 2013). If one tries to understand emotion (in our case, arousal) from still images, one is very likely to miss important information available through context, or surroundings of the person. It might be helpful to look at the entire video segment and annotate the affective state of a

person during PEERS intervention. Moreover, this annotation, if done by behavioral expert/s can add a more reliable perspective to the research.

5. DESIGN AND VALIDATE A SOCIAL SKILLS INTERVENTION FOR CHILDREN WITH ASD

5.1 Motivation

Children with ASD may have an affinity for mobile computing device (AHRQ, 2014), which may be useful for providing evidence-based therapies (Flores et al., 2012). However, every child with ASD is different and therefore each child will benefit from an individualized teaching approach (Mesibov et al., 2004). Moreover, some teaching techniques are specific to teaching children with ASD, for example breaking down an activity into steps, replacing words with pictures, making complicated things seem simple, avoiding distractions in terms of sound, light, etc. (Kagohara et al., 2013). It is believed that with effective treatment and intervention, many children with ASD will improve their level of functioning (AHRQ, 2014; Kagohara et al., 2013).

With the advancement in mobile technologies, the learning environment is no longer restricted to classrooms and paper-based materials. Mobile devices provide a flexible way of learning where the content, timing, and location of a learning schedule can be arranged according to the user's preference (Peters, 2009; Sharples, Taylor, & Vavoula, 2005). A mobile device is usually equipped with a camera, microphone, and speaker, which can aid in content design. With these features, mobile technology has led to the growth in the development of educational software. This software, in the form of application software or mobile games, can be designed according to the specific needs of a user or customer.

Flashcards are widely used as an instruction medium for teaching specific skills, for example, reading, spelling, and phonetics. Moreover, flashcards have been shown to be an effective method for teaching children with learning disabilities, such as ASD (Erbey, McLaughlin, Derby, & Everson, 2011; Hayter, Scott, McLaughlin, & Weber, 2007; Hopewell, McLaughlin, & Derby, 2011; L. Kaufman, McLaughlin, Derby, & Waco, 2011). Flashcards are used to teach a wide variety of topics, from simple mathematics to historical dates, or from sight words to scientific formulas. The flashcard-based system and mobile technology can be combined, in order to get the maximum benefits of these two learning approaches.

iCanLearn is a mobile-based flashcard application which can be used to teach social skills to children with ASD. This app provides you the flexibility of designing user-specific content with the use of text, pictures, and audio recording. One can connect multiple devices over wi-fi in order to maintain a teacher-student relationship. This app is easy to use, which is fundamental to the successful acceptance of any kind of assistive technology (Marcu, Dey, & Kiesler, 2012). After the design and development of this mobile –based learning technique was complete, an evaluation study was also carried out. The goal of this study is to validate if the social skill application intervention was able to provide an acceptable learning environment for children.

5.2 Methods

The aims of this study were to investigate 1) the usability of a new learning application, in terms of its features and design considerations, and 2) the changes in the level of anxiety experienced by parents or primary caregivers of children with ASD while using the application.

5.2.1 Participants

Parents or primary caregivers of children with ASD were invited to participate in this study. The subjects were contacted by posting the information about this study in several newsletters, such as Autism Society of Southeastern Wisconsin (ASSEW) and Waukesha County – Children with Special Needs Unit. The email containing information about the study was forwarded to the group of people who previously indicated interest in receiving information about such opportunities. Table 5-1 provides the demographic information of the participants who took part in this evaluation study.

Participant ID	Gender	Age Range (yrs)	Marital Status	Highest Level of Education	Child's Age (yrs)
ICL01	Female	35-44	Divorced	Some College	18
ICL02	Female	65 and over	Married	4-Year College Degree (BA/BS)	3-16*
ICL03	Female	35-44	Married	4-Year College Degree (BA/BS)	10
ICL04	Male	35-44	Married	Master's Degree	5
ICL05	Female	25-34	Married	4-Year College Degree (BA/BS)	6
* indicates that the participant worked as consultant with several children					

Table 5-1: Demographic Information of Participants – iCanLearn Evaluation

5.2.2 Measures

Since parenting a child with ASD can be demanding and comes with its unique anxiety producing stresses (Simonoff et al., 2008), using a new technology could also be overwhelming for parents. This study aimed to see if using the ‘iCanLearn’ app had any adverse effects on the anxiety being experienced by parents. For examining the changes in anxiety experienced by individuals, the six-item short form of the Spielberg State-Trait

Anxiety Inventory (STAI) (Marteau & Bekker, 1992) was used. This six-item form is a self-rating scale and has been validated for providing similar scores to those obtained using the full 20-item STAI. It has satisfactory reliability and is useful in cases of time constraint. The six-items include both anxiety-present and anxiety-absent items, and were rated on a four-point Likert-type scale.

To assess the usability of ‘iCanLearn’ app, a web-based survey tool was created for the study. This survey had 16 questions related to user experience (see Table 5-2) and 8 questions on that collected demographic information to describe the participants.

Items		Options (n*)					
1	Which of the following devices do you use on a regular basis?	iPhone (2)	iPad (1)	Both (2)			
2	For how long have you been using an iPhone?	3 months, 1 yr. 8 months, 3 yr. 2 months, 2 yrs.					
3	For how long have you been using an iPad?	1 year, 1 yr. 6 months, 6 months					
4	How would you rate your comfort level with downloading, installing and using an application on your iPhone/iPad?	Excellent (0)	Very Good (3)	Good (1)	Fair (1)	Poor (0)	Very Poor (0)
5	Do you think that iCanLearn app is easy to use?	Strongly Agree (3)	Agree (2)	Disagree (0)	Strongly Disagree (0)		
6	Do you feel that users of iCanLearn should be provided with an in-person demonstration on	Strongly Agree (0)	Agree (0)	Disagree (3)	Strongly Disagree (2)		

	how to use this app (iCanLearn)?						
7	Which of the following features of iCanLearn have you used in creating slides for your child? (Check all that apply)	Text (4)	Picture (5)	Audio Recording (3)			
8	Do you feel that iCanLearn provides you flexibility in designing the content of the skill that you want to teach your child?	Strongly Agree (1)	Agree (4)	Disagree (0)	Strongly Disagree (0)		
9	How many times have you used iCanLearn in the past two weeks?	1-3 times (2)	4-6 times (2)	7-10 times (1)	11+ times (0)		
10	List the different scenarios in which you have used iCanLearn (e.g. - to teach how to brush your teeth, how to get ready for school, how to greet someone, etc.)	Do laundry, Wash dishes by hand, Beginning of the day routine, Toileting routine, Waiting your turn, How to brush teeth, Putting back toys and other stuff					
11	Have you and your child used iCanLearn on two different devices connected in Teacher-Learner mode over a Wi-Fi network?	Yes (2)	No (3)				
12	If yes, how many times have you used iCanLearn in Teacher-Student	1-3 times (2)	4-6 times (0)	7-10 times (0)	11+ times (0)	Not Applicable (3)	

	mode in the past two weeks?						
13	Do you feel that your child is able to learn from iCanLearn on his/her own?	Strongly Agree (0)	Agree (5)	Disagree (0)	Strongly Disagree (0)		
14	Based on your experiences, would you recommend iCanLearn app to others?	Definitely (4)	Probably (1)	Maybe (0)	Probably not (0)	Definitely not (0)	
15	What, if anything, about iCanLearn really pleased you?	Super easy and fast to build flashcards, Ease of use, has text, picture and audio features, nice graphics					
16	What, if anything, about iCanLearn really disappointed you?	I had to label the slides (a., b., c., etc.) to put them in sequential order					
*indicates the number of participant who selected that option							

Table 5-2: User Experience Questionnaire from the iCanLearn Evaluation Study

5.2.3 Procedure

The approval for this study was received from the University's IRB (Institutional Review Board). The study was conducted in two parts – Pre-Survey and Post-Survey. The participants were provided with a link to a web-based survey (Pre-Survey). This link provided the participants an opportunity to consent electronically before being directed to the pre-survey. Informed consent was obtained prior to data collection. Participants were provided with the contact information of researchers working on this project, so they could ask questions.

The pre-survey questionnaire was aimed to assess the anxiety being experienced by a parent or caregiver, as regards teaching a new skill to their child with ASD. They were told to think about a situation where they were trying to teach a social skill or any daily activity to their child. They were asked to self-rate themselves on a six-item short form of the STAI. They were then given instructions on how to install the mobile app ‘iCanLearn’ on their Apple devices (iPhone or iPad). They were advised to use the app as many times as possible for next two weeks. The only personal information collected from the participant was his/her email address. This email address was used to contact that participant to provide him/her with the link to another web-based survey (Post-Survey) as well as the reward email. At the end of two weeks, they were contacted individually via email containing the post-survey link. The Post-survey was comprised of 3 parts: 1) self-evaluation for measuring the anxiety level experienced by the subjects while teaching a certain activity to their child knowing that the mobile application could be used to their aid, 2) evaluation of the mobile application in terms of ease of use, features and overall user experience and 3) demographic questionnaire for statistical purposes. Each participant was given an Amazon.com gift card worth \$15 after the completion of the Post-survey to compensate them for their time.

5.2.4 Results

For the initial survey, there were 20 participants and 5 of these also completed the Post-survey questionnaire. The participants’ anxiety level before and after using the ‘iCanLearn’ app did not increase in any of the participants. Figure 5-1 shows the comparison of pre (blue bars) and post (orange bars) anxiety scores of the 5 participants.

Table 5-2 shows the results of users' experience with iCanLearn (the number in parentheses indicates the number of participants who selected that particular option).

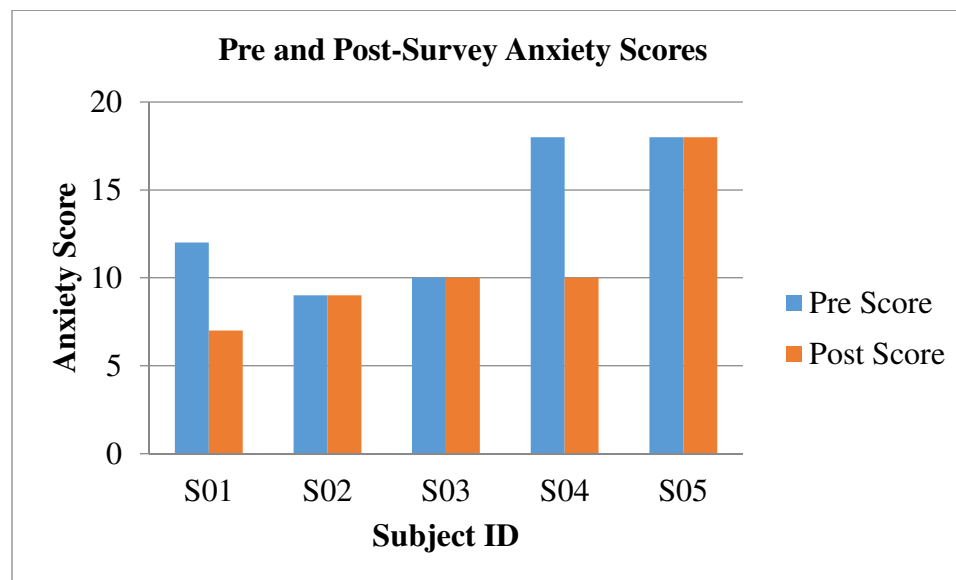


Figure 5-1: Pre-Study and Post-Study Anxiety Scores

The participants also provided the researchers with different scenarios in which they tried using the app such as doing laundry, washing dishes by hand, morning or toilet routine, waiting your turn, brushing teeth, putting back toys, etc. All the participants unanimously agreed that the app was easy to use for parents, as well as their children. In fact, parents found it so easy to use that they all declined the in-person demonstration on how to use the app. The participants felt that the app was easy to use from a child's perspective, as well. Favorable feedback obtained from participants included the following information about the usefulness of the 'iCanLearn' app:

“...I made a set for washing dishes, 6 steps. It took about 5 minutes to build it, SO easy, and fun! You just snap a picture, record your instruction, and give it a title. It could not be any easier. I love it!”

“It was a pleasure to participate in the study, and I will continue to use the app.”

One participant commented that the slide titles he created for each slide subsequently determined the order of the slide presentation, alphabetically. There was no instruction that the participant should have numerically labeled each slide in order to keep slides in correct sequence. This was a very helpful comment and the instructions now indicate that the titles should begin with a number to keep them in order.

5.3 Discussion

The first aim of our study was to examine the change in anxiety level of parents of children with ASD before and after using the mobile app – iCanLearn. From our study, it was found that using the app did not have any adverse effect on the anxiety level of parents. The anxiety level after using the app either remained unchanged or it decreased from the level experienced before using the app. The second goal of the study was to assess the usability of this app in terms of its design and features. The qualitative responses provided by the participants indicated the ease with which this app was used by children and their parents alike. This ease of use likely stems from the design considerations behind this project.

The evaluation of the app has limitations. The sample size is small. Since this app comes with a social benefit, there was no desire to restrict the users from using this app by

first launching a trial version for this study. After the pre-survey, once the users got to know about the app and what it could be used for, the \$15 gift card did not appear to be enough of an incentive for them to participate in the second part of the study. The data received, even with the small sample, was helpful, especially the comment on the numbering of the slides. The users' range of topics for the social stories and flashcards, as well as the comment about not needing an in person demonstration of how to use the app, validate the acceptability and feasibility of the app. There is a real potential that iCanLearn could have a broad impact on our society by improving the way we conduct and personalize autism interventions and education.

6. DESIGN, DEVELOP AND DEPLOY AN AUTOMATED SCREENING TOOL FOR ASD

6.1 Motivation

The National Alliance for Autism Research (NAAR) conducted a poll in 2007 with the aim of measuring awareness of autism among Americans. These poll results highlight the fact that Americans not only have low level of knowledge about ASD, but also have certain misconceptions about this disorder (NAAR, 2007). With a lack of knowledge about this developmental disorder, it is likely that many individuals might not know the signs that a child with ASD might be showing in his/her early childhood. Research shows that the early signs of autism can be evident from as early as 6 months of age (Bolton, Golding, Emond, & Steer, 2012). Although there is no cure for ASD, outcomes and the effectiveness of interventions can be improved if screening and diagnosis is done earlier in life.

Developmental assessment by pediatricians is an effective and widespread method for screening children for ASD (Robins & Dumont-Mathieu, 2006). However, despite the existence of well-designed screening tools for ASD, most physicians do not complete screening for ASD (Dosreis, Weiner, Johnson, & Newschaffer, 2006), even though it is recommended by the American Academy of Pediatrics (Johnson & Myers, 2007). There are several reasons behind this, such as lack of required training, time constraints, reimbursement issues, and discomfort in handling positive screens and/or parental reactions (Pinto-Martin, Dunkle, Earls, Fliedner, & Landes, 2005). Thus, this study was designed to develop a tool to make diagnostic screening simpler and more

available to healthcare providers and families, while also providing a direct link from families and health care providers to ASD diagnosticians after positive screens.

6.2 Methods

6.2.1 Measures

The Modified Checklist for Autism in Toddlers (M-CHAT) is a validated screening tool for assessing the risk of ASD in toddlers between the age of 16 and 30 months (Robins, Fein, Barton, & Green, 2001). The M-CHAT, Revised, with Follow-up (M-CHAT-R/F) is a two-stage parent-report screening tool (Robins, Fein, & Barton, 2009), where M-CHAT-R with 20 items can be administered during well-child visits. A follow-up interview must be conducted for positive screens on M-CHAT-R. This checklist along with scoring guide is available for free download, but the permission was given for the present study to reproduce it in electronic form along with relevant pictures to explain the item more clearly (application picture credits: Yoko Camio, Japan, and Patricia Garcia Primo, Spain).

6.2.2 Procedure

An mHealth-based, picture-enhanced version of M-CHAT-R diagnostic tool for early screening of Autism Spectrum Disorder will be developed. The questionnaire would be accessible from any web-enabled mobile device such as a laptop, tablet, or smartphone. Moreover, each question would be accompanied by a relevant picture/s so as to make it easily understandable.

A mobile version of the M-CHAT diagnostic tool makes it more accessible and can be disseminated widely. In our project setting, the mobile device with pre-loaded

questionnaire page would be given to the parent/caregiver of the child while they are waiting for the health care professional (HCP) in the examination room during the 18 and 24 month well-child visits. Once the questionnaire has been completed, the user would be given a brief summary of the screening result and what could be done next. In the case of a positive screen for the risk of ASD, the user is asked to give their consent for the screening results and contact details to be sent to an ASD diagnostician for further evaluation. As soon as the informed consent is obtained, all the information about the user and the questionnaire response will be stored in the database. When the database receives a positive screen, an alert notification will be generated and sent to the ASD diagnostician. The ASD diagnostician would then contact the family for follow-up screening with the second part of the M-CHAT R/F. The results page of the tool (both positive and negative screens) will have a “PRINT” button. This will allow the HCPs to take a hard copy of the screening results for review and can be scanned in the Electronic Medical Record. The screen layout for this automated tool can be seen in Appendix C.

The features needed in order to accomplish our research aims are in place. Once the above-mentioned tool is designed and developed, the system will be tested. After the initial testing is done, the system will be deployed with the help of local pediatricians’ offices and ASD diagnosticians.

6.3 Discussion

This automated tool improves care in two significant ways: first, the automated scoring of items on the questionnaire reduces the burden on doctors and/or nurses for scoring a screening tool. Second, the automated reporting of scores to the regional ASD

diagnostician facilitates timely family access to follow-up with a specialist for comprehensive diagnostic evaluations.

Research goals are set for this study. An understanding of the features needed for the automated tool is complete, and permissions to use and adapt the M-CHAT R/F have been gained from the developer of the original tool. The next step would be to develop the tool. After initial testing, the tool will be deployed and made available for use to relevant parties. An evaluation study will then follow.

7. CONCLUSION

7.1 Summary

In this dissertation, an introduction to the research work was first provided. Brief background information on each of the key concepts involved was then presented. Next, an explanation in detail was provided for the set-up for the three research problems centered on ASD. For the first research problem, it was found that, although the adolescents with ASD endorsed the presence of physiological arousal through EDA data, facial expressions were not predictive of their arousal states. A significant relationship between EDA data and self-anxiety score indicated that the participants were self-aware of the arousal. In an attempt to compare the accuracy with which humans and machines could interpret the arousal state from facial images of adolescents with ASD, it was found that the machine algorithms were better at labeling the high and low arousal images than humans were at the same task. This study was an attempt to have a better understanding of emotions in individuals with ASD. In the next research problem, the results of an evaluation study for a mobile-based social skill intervention was presented, which suggested that the intervention was very well accepted by the intended users. The application obtained good feedback in terms of its usability and did not adversely affect the anxiety level of parents or caregivers of children with ASD. Lastly, the design goals of an automated tool for screening of ASD in toddlers were proposed. This tool could facilitate a screening process with less effort from doctors and staff. Moreover, in the case of positive screens, the tool has the capability to connect the family with follow-up

diagnostic evaluations from a specialty ASD clinic. This system can pave a way for early diagnosis and treatment of ASD.

7.2 Contributions of Dissertation

This dissertation has investigated several aspects of Autism Spectrum Disorder using computational methods. The major contributions of this work are:

- Examined a multimodal method for studying physiological arousal among adolescents with ASD in a naturalistic environment.
- Used computational methods to examine how the different modalities of this study related to one another.
- Examined whether humans were more or less proficient at understanding the expression of arousal from facial images of adolescents with ASD, as compared to a machine or a computer.
- Listed and evaluated the features required by a learning app to be an effective intervention tool for children with ASD.
- Designed an effective screening tool for ASD by providing a linkage between positive screening and diagnosis evaluations at a specialty clinic.

7.3 Future Work

Understanding the physiology of individuals with ASD, in relation to expression of emotions via the face, is a very novel and challenging task. In this dissertation, a specific setting (PEERS intervention) was used for data collection. It will be interesting to see how the participants respond in other environments, like, home, school, etc. Also, a comparison study with a typically developing group is under consideration. Once a

stabilized system is developed, with desired level of accuracy for monitoring the physiology of participants, the development of home-based monitoring tools can be considered for a better understanding of arousal and associated emotions. It would be worth investigating if the performance of an individual in an intervention is affected by the presence of physiological arousal.

LIST OF PUBLICATIONS

Papers:

- **Jain, N.**, Van Hecke, A.V., Ahamed, S., Bozdog, S., Stevens, Casnar, C.L., Caiozzo, C., S., Dolan, B., & Potts, S (2015). Multimodal measurement of physiological state in intervention for adolescents with ASD: feasibility and link among domains. Submitted to *IEEE Transactions on Biomedical Engineering (TBME)*.
- Zaffke, A., **Jain, N.**, Johnson, N., Alam, M. A. U., Magiera, M., & Ahamed, S. I. (2015). iCanLearn: A mobile application for creating flashcards and social stories™ for children with autism. *Smart homes and health telematics* (pp. 225-230) Springer.
- Adibuzzaman, M., **Jain, N.**, Steinhafel, N., Haque, M., Ahmed, F., Ahamed, S., & Love, R. (2013). In situ affect detection in mobile devices: A multimodal approach for advertisement using social network. *ACM SIGAPP Applied Computing Review*, 13(4), 67-77.
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- Haque, M. M., Adibuzzaman, M., Polyak, D., **Jain, N.**, Ahamed, S. I., & Liu, L. (2011). IRENE: Context aware mood sharing for social network. *Service-Oriented Computing and Applications (SOCA), 2011 IEEE International Conference On*, 1-8.

Posters:

- **Jain, N.**, Ahamed, S., Stevens, S., Schohl, K.A., Dolan, B., McVey, A.J., Potts, S., Casnar, C.L., Caiozzo, C., Vogt, E.M., & Van Hecke, A.V. (2015). Physiological monitoring during PEERS®: A "culture-free" method of understanding intervention response. Poster at *International Meeting of Autism Research (IMFAR)*, May 14-16, 2015, Utah, USA.
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APPENDIX A: Sample Survey for Psychology Subject Pool Study

Please provide the following information:

Code Number: _____

The following questions are for statistical purposes only. The information you provide here is strictly confidential.

1. What is your sex?
 Male Female

2. What is your age?
 18 years 19 years 20 years 21 years 22 years and over

3. Which of the following best describes your racial or ethnic background?
 Asian
 Black/African American
 White/Caucasian
 Hispanic (may be any race)
 Native American
 Other. Please Specify: _____

4. What is your current school year?
 Freshman Year
 Sophomore Year
 Junior Year
 Senior Year

5. What is your approximate family income before taxes?
 Under \$10,000
 \$10,000 to less than \$20,000
 \$20,000 to less than \$35,000
 \$35,000 to less than \$50,000
 \$50,000 to less than \$75,000
 \$75,000 to less than \$100,000
 \$100,000 or more

Continued...

Please rate the following images on the basis of AROUSAL* (high or low) and VALENCE§ (positive or negative).

* Arousal indicates the level of physical response

§ Valence indicates the direction of emotion



Image 001

Arousal

- High
- Low

Valence

- Positive
- Negative

APPENDIX B: PowerPoint Slide Explaining Arousal and Valence with Examples

Arousal indicates the level of physical response

Valence indicates the direction of emotion

Some examples:


Emotion	Arousal	Valence
Angry	High	Negative
Bored	Low	Negative
Calm	Low	Positive
Depressed	Low	Negative
Excited	High	Positive
Frustrated	High	Negative

APPENDIX C: Screen Layout for mHealth-based M-CHAT Screening Tool

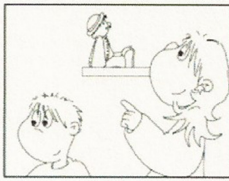
M-CHAT-R/F

Please fill out the following about your child's usual behavior, and try to answer every question. If the behavior is rare (you've only seen it once or twice), please answer as if your child does not do it.

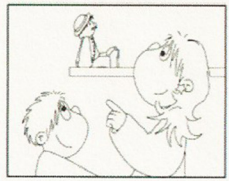
© 1999 Robins, Fein & Barton
Image Courtesy: Yoko Camio and Patricia Garcia Primo

 1

1. If you point at something across the room, does your child look at it? (for example, if you point at a toy or an animal, does your child look at the toy or animal?)



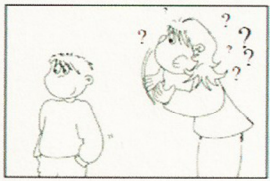
✓ Yes



✗ No

➡ 2

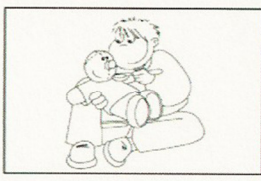
2. Have you ever wondered if your child might be deaf?



✓ Yes ✗ No

➡ 3

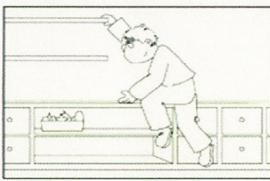
3. Does your child play pretend or make-believe? (for example, pretend to drink from an empty cup, pretend to talk on a phone, or pretend to feed a doll or stuffed animal?)



✓ Yes ✗ No

➡ 4


4. Does your child like climbing on things? (for example, furniture, playground equipment, or stairs)



✓ Yes ✗ No

➡ 5

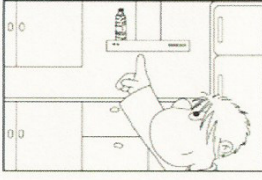
5. Does your child make unusual finger movements near his or her eyes? (for example, does your child wiggle his or her fingers close to his or her eyes?)



✓ Yes ✗ No

➡ 6

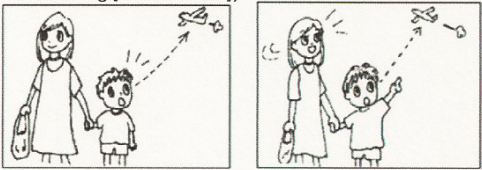
6. Does your child point with one finger to ask for something or to get help? (for example, pointing to a snack or toy that is out of reach)



✓ Yes ✗ No

➡

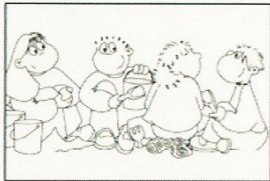
7. Does your child point with one finger to show you something interesting? (for example, pointing to an airplane in the sky or a big truck in the road. This is different from your child pointing to ASK for something [Question #6.]



✓ Yes ✗ No

➡

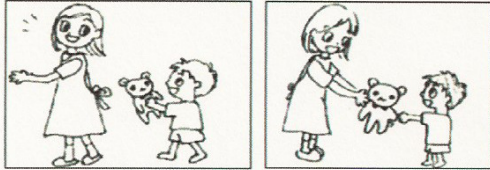
8. Is your child interested in other children? (for example, does your child watch other children, smile at them, or go to them?)



✓ Yes ✗ No

➡


9. Does your child show you things by bringing them to you or holding them up for you to see - not to get help, but just to share? (for example, showing you a flower, a stuffed animal, or a toy truck)



✓ Yes ✗ No

➡


10. Does your child respond when you call his or her name? (for example, does he or she look up, talk or babble, or stop what he or she is doing when you call his or her name?)



✓ Yes ✗ No

➡

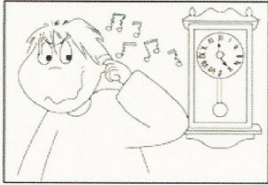
11. When you smile at your child, does he or she smile back at you?



✓ Yes ✗ No

➡

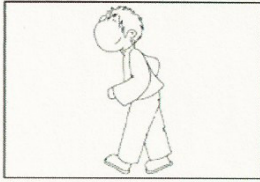
12. Does your child get upset by everyday noises? (for example, does your child scream or cry to noise such as a vacuum cleaner or loud music?)



✓ Yes ✗ No

➡₁₂

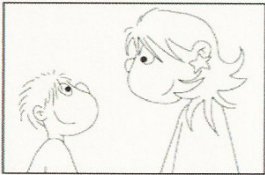
13. Does your child walk?



✓ Yes ✗ No

➡₁₃

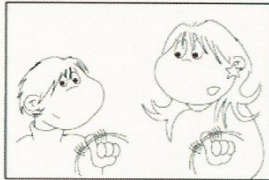
14. Does your child look you in the eye when you are talking to him or her, playing with him or her, or dressing him or her?



✓ Yes ✗ No

➡₁₄

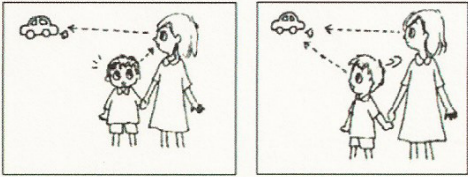
15. Does your child try to copy what you do? (for example, wave bye-bye, clap, or make a funny noise when you do)



✓ Yes ✗ No

➡₁₅

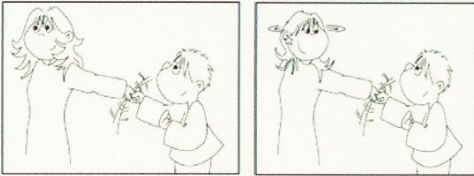
16. If you turn your head to look at something, does your child look around to see what you are looking at?



✓ Yes ✗ No

➡₁₆

17. Does your child try to get you to watch him or her? (for example, does your child look at you for praise, or say "look" or "watch me"?)



✓ Yes ✗ No

➡₁₇

18. Does your child understand when you tell him or her to do something? (for example, if you don't point, can your child understand "put the book on the chair" or "bring me the blanket"?)

✓ Yes ✗ No

➔

19. If something new happens, does your child look at your face to see how you feel about it? (for example, if he or she hears a strange or funny noise, or sees a new toy, will he or she look at your face?)

✓ Yes ✗ No

➔

20. Does your child like movement activities? (for example, being swung or bounced on your knee)

✓ Yes ✗ No

Submit 21

In case of positive screen at risk for autism, the next screen/page will look something like this:

22

Your child may be at the risk for Autism Spectrum Disorder (ASD) or other developmental delays. Please fill out the following for someone to contact you about following up on these results.

Name

Phone No.

Email

Clicking on the "Agree" button, indicates that you give us the permission to contact you via the contact information provided here. Clicking this button will also send your response to the questionnaire and contact information to the Autism Clinic. You will then be contacted by a specialist for further evaluations on your child's development.


Agree Disagree and Exit

You may print a copy for your record PRINT 23

In case of negative screening, the next screen/page (after Question 23) will look something like this:

24

There are no concerns with your child's development. Please continue the developmental surveillance. If you have any questions, please contact us at the following email address:
XXXXXXXXXXXX

You may print a copy for your record  **PRINT** 25