Using Physiological Signals and Machine Learning Algorithms to Measure Attentiveness During Robot-Assisted Social Skills Intervention: A Case Study of Two Children with Autism Spectrum Disorder

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Individuals with autism spectrum disorder (ASD) often face barriers in accessing opportunities across a range of educational, employment, and social contexts. One of these barriers is the development of effective communication skills sufficient for navigating the social demands of everyday environments. Fortunately, researchers have established evidence-based practices (EBP) for teaching critical communication skills to individuals with ASD [1]. One EBP that has received a great deal of attention over the last few decades is technology-aided instruction and intervention (TAII) [1],[2]. TAII is an instructional practice in which technology is an essential component and is used to facilitate behavior change. Further, it encompasses a wide range of applications including computer-assisted instruction, virtual and augmented reality, augmentative and alternative communication, and robot-assisted intervention [2].

Over the last two decades, there has been increased interest in the application of robot-assisted interventions (RAI) for teaching social skills to learners with ASD [3]. RAI involves the use of robots to deliver, augment, or support intervention practices. Researchers have employed robots to teach a myriad of social skills including joint attention [4], text messaging [5], interpreting and making gestures [4], and emotion recognition [6]. During RAI, robots can serve as direct instructional agents, emitting directives or modeling targeted behaviors. For example, Pennington and colleagues used an autonomous, programmable humanoid (NAO) robot to verbally direct students how to generate text messages [5]. The robot provided a directive to the participant, waited for the participant to indicate they were finished prior to emitting the next directive, and then offered to perform a dance at the end of the session. Similarly, another study used an NAO robot to assist in facilitating game scenarios during pivotal response training [7]. During sessions, therapists controlled the robot to present stimuli, prompt participants to respond, and provide reinforcing feedback. The application of robots as change agents during social skills intervention may offer several benefits including increasing the reinforcing properties of intervention packages, limiting human errors in implementation fidelity, and reducing social requirements of interpreting subtle social cues emitted by the human instructors (e.g., facial expression, changes in intonation).

The majority of investigations in which a robot served as an instructor involved the programming of one-way (e.g., robot presents a directive and the child responds) and two-way (e.g., robot presents a vocal directive, the child responds, the robot detects response and provides feedback or emits next directive) interactions, or a *Wizard of Oz* approach in which the instructor directs the actions of the robot. These approaches are limited in that they rely on an external human change agent to observe, detect, and respond to subtle changes in the learner's attention; attention is essential to skill acquisition and may be difficult for some learners with ASD. This reliance on an additional human change agent to facilitate attention during robot-learner interactions ultimately serves as a barrier to the autonomous application of robots to support student learning.

A way to address this issue is by incorporating software to detect and respond to physiological correlates for attention within RAI packages. Physiological signals can be an especially useful communication link for children with ASD, whose outward expressions of affect may not be as apparent as developmentally typical children [8]. However, the implicit physiological signals of children with ASD do indicate emotional changes to stimuli, including during social interactions [8].

Researchers in affective computing have reported physiological signals to be a reliable source of objective information related to users' emotional reactions, because of the signals' connections to the autonomic nervous system [8]–[12]. However, conducting affective computing research presents challenges in data collection. For example, although computer vision could be used to process video streams of users and their reactions [13], this signal presents privacy issues and poses a challenge of collecting video from certain (e.g., preferably head-on) angles at all times [13],[14], whereas privacy is less of a concern with wrist-worn devices [15]. Additionally, some physiological signals are more cumbersome to collect than others and lead to less adoption rates by users [16], such

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as electroencephalogram which can involve skull caps and conductive gel on a user's head or respiratory data collected from a strap wrapped around a user's upper chest. Some signals may be slow to change as compared to others, such as respiratory signals compared to heart rate variability, and therefore limit a closed-looped system's ability to respond quickly to a user's change in emotion [14]. Although these signals may provide informative data that can be related to emotions [11],[14], their data collection techniques may limit the type of natural user interactions that can be studied [15] and may preclude the adoption of these sensors in a user's daily life [13],[16], thus limiting the future capacity of affective computing to be applied to everyday life. Therefore, ambulatory measurement from sensors with a high adoption rate by users is preferable [8],[17]. Collecting physiological signals from a wristband device addresses many of the data collection challenges in affective computing research.

Empatica's E4 is a commercially available wearable device with embedded sensors that was developed by affective computing researchers [18] and has been used in several studies to examine affect and physiological signals [11],[19]. The E4 is one example of how much physiological-sensing equipment has evolved in the last decade [8],[16] and matches the characteristics of an appropriate wearable sensor suggested for use with the ASD population [20]. Wires have been reduced or eliminated, and sensors covering several fingertips (which limited the types of activities a user could do and therefore an experimenter could study) have been rendered unnecessary with advancements in the ability to collect robust data from the wrist and transmit it wirelessly. These improvements have greatly increased our capacity for measuring on-the-go.

The E4 collects signals produced by the body's electrodermal activity (EDA), skin temperature (SKT), and blood volume pulse (BVP) and provides a feature calculated from BVP as a continuous signal: heart rate (HR) [11]. These signals have been studied in related research [10], [20]. Based on previous research [9],[12], we extract several features from these four signals, as described further in the feature extraction process section.

Analyzing physiological correlates requires the use of machine learning algorithms that can detect changes in these correlates with high levels of accuracy. Direct correlation analysis that detects only linear relationships between signals and affect, and static rules defining when a threshold is crossed, limit the type of patterns that can define an affective state of interest [17]. However, machine learning algorithms can recognize non-linear patterns and leverage high-dimensional dataspaces [9],[10],[13],[17]. An effective algorithm would: predict between affective states of interest with accuracy better than chance; have an area under the curve (AUC) as close to one as possible; and have a variance between training and testing results as close to zero as possible. The purpose of the current case study was to evaluate algorithms in the context of RAI to determine their potential efficacy in determining when students are attentive during RAI-related tasks. We addressed the following two research questions: Do physiological signals indicate different affective states of children with ASD during RAI? And How accurate are machine learning algorithms, built from physiological signals, at matching expert coders when differentiating between levels of attention by children with ASD?

In this investigation, we sought to evaluate algorithms in the context of RAI to determine their potential efficacy in determining when students with ASD are attentive during RAI-related tasks. We calculated features from physiological signals collected by an E4 and compared the performance of four machine learning algorithms commonly used in affective computing. Our findings indicated the E4 data were useful for categorizing states of attentiveness in children with ASD.

Method

Participants and Setting

We recruited participants through a university-affiliated autism clinic that regularly conducted social skills groups for children with ASD. We obtained parental consent and participant assent prior to the study. Two children with ASD (i.e., Cody and Max), age 11 years, participated in the investigation. Both participants were diagnosed as having ASD, using the *Autism Diagnosis Observation Schedule-2*, and identified to have difficulties in initiating and maintaining social interactions. Both participated in a social skills group at the autism clinic.

We observed and collected data samples during 5-min observations of social skills group activities that took place over several weeks. Due to the availability of only two E4s, we only included two participants in the study. Specifically, we collected data during a pilot evaluation of RAI and unstructured social interaction probes. During RAI, the children with ASD were seated in front of an NAO robot (Fig. 1) and directed to engage in scripted interactions. During the social interaction probes (SIP), the children with ASD were seated around a table and directed to talk with each other.

Fig. 1. An NAO robot sits on a cart, ready to interact with children during the social skills intervention.

Materials and General Procedures

During the investigation, the participants wore the E4 on their nondominant wrist, with the EDA electrodes on the underside of the wrist and in line between the middle and ring fingers. We used the E4 to collect data during RAI and SIP that occurred at the onset of each meeting of a 12-week social skills group. Upon arrival at the autism center, social skills group members, including the two participants, were brought to a multipurpose room. We placed the E4s on the participants' wrists and similar but nonfunctional devices on the other children's wrists. Next, we implemented RAI and SIP sessions, and then the children attended their social skills group. At the end of each group meeting, we collected E4 data during a 3-min period of quiet sitting. This daily baseline recording was gathered for use in the normalization step of processing the physiological signals. We also collected behavioral observation data from video recordings of the sessions.

Measurement

We collected data on whether participants were attentive or inattentive during sessions using both behavioral observation and physiological signals. For behavioral observations, attentiveness was defined as on-task, attending to the activity, and responding to directions. Inattentive was defined as the subject being off-task, inattentive to the activity at hand, and not responding to directions. We divided observation periods into 20-s intervals of our video recordings, and observers scored participants as being attentive or inattentive for each interval collected. They based their score on their observation for the majority of each 20-s interval. For example, for a given 20-s video clip, if a participant exhibited a moment of being on-task but was otherwise not responding to directions for the majority of the 20-s interval, then the sample was scored as inattentive. Observers were trained coders from a university research center with extensive experience in classroom observation of children with disabilities. In addition, the first author also coded a sample of 30% of the intervals to assess interrater reliability. These randomly selected intervals were selected from an equal number of samples across participants and sessions. We used Cohen's Kappa to calculate reliability. The Cohen's Kappa statistic is commonly used to test interrater reliability and is advantageous in that it accounts for chance agreement between raters [21]. We calculated interrater reliability to be 81.7%.

Feature Extraction Process and Data Analysis

Using the E4, we processed 20-s intervals to extract features that could indicate changes in affect. The features are derived from physiological signals using signal-processing techniques employed in previous work [12]. Data vectors were made of 12 normalized physiological features extracted from four signals. The peaks of the BVP signal were detected, and two features were calculated: mean of the peak amplitudes and maximum peak amplitude. Two features, the mean and standard deviation of HR, were calculated. For EDA, the tonic and phasic components were processed [22], and five features extracted: mean of tonic skin activity, slope of tonic activity, peak rate of phasic activity as peaks per minute, mean of phasic peak amplitudes, and maximum peak amplitude of phasic activity. Three features from SKT are mean, standard deviation, and slope of SKT. These features showed significant responses in previous research [9],[11],[19], and are therefore well vetted in the study of physiological signals in relation to affective computing. Moreover, previous research included social interaction activities for children with ASD [12], and therefore, these features are likely for consideration to indicate affective states during similar activities and populations.

The feature extraction process provides feature vectors, each a length of 12 features. To account for day variability in physiological signals, the intervals were adjusted using the baseline from each meeting. After calculating the mean absolute deviation, the interval with the least variability for a given meeting day, per signal, was chosen to serve as the baseline recording for day variability correction of the feature vectors. The feature vectors were then min-max normalized across vectors, per subject and feature-wise. After accounting for day variability and normalizing the data, subject Cody had 293 feature vectors, and subject Max had 250 feature vectors. These feature vectors were sent to machine learning algorithms for classification.

The feature vectors for each subject were used as inputs into machine learning algorithms, which were trained to differentiate between the affective states of attentive and inattentive. We compared four algorithms commonly used in affective computing: Logistic Regression (LR), Support Vector Machines (SVM), ensemble-based Random Forest (RF), and ensemble-based Gradient Boosted Regression Trees (GBRT) algorithms. All of the machine learning models were implemented in Python using scikit-learn 0.24.2.

Before we built models, we split the dataset into separate training and test sets. We created sets of a typical percentage split of 80/20 for training/test sets, after taking steps to maintain as much of the natural data as possible while also over-sampling with synthetic data to balance the classes. The test set was created by randomly shuffling and selecting 50% of the data points from the minority class, in this case the inattentive class. Another random shuffle selected an equal amount of data points from the majority class, in this case the attentive class, to create a balanced test set with natural data. Table 1 summarizes the class distributions between the original, training, and test sets sent to the algorithms.

The four models were fit to the training data, and we used a stratified 5-fold cross-validation scheme to prevent overfitting the model and ensuring generalization to the test data. To combat the class imbalance, we applied the Smote+Tomek-link (Smote+TL) over- and under-sampling technique to the training split. We fit the model to the resampled training split and measured the performance using the validation split. We repeated this process k times (i.e., 5) and averaged the results to get a performance metric. Smote+TL was implemented in Python using the imbalanced-learn 0.8.0 package [23].

Table 1 – Class distributions in the data sets are described for each subject				
Data Set	**Class**			
	Cody		**Max**	
	Attentive	**Inattentive**	**Attentive**	**Inattentive**
Original	222	71	197	53
Test	**35**	**35**	**26**	**26**
Training sets available	187	36	171	27
Over- and Under-sampling Training sets to balance classes	**140** (140 Natural 0 Synthetic) *under-sampling*	**140** (36 Natural 104 Synthetic) *over-sampling*	**104** (104 Natural 0 Synthetic) *under-sampling*	**104** (27 Natural 77 Synthetic) *over-sampling*
80/20 Training/Test	140/35	140/35	104/26	104/26
Total data sets sent to algorithms	**175**	**175**	**130**	**130**

Several performance metrics can be used in a binary classification problem, but it was important to use a metric that would capture the performance of both classes. The receiver operating characteristic (ROC) is a common method to visualize the performance of a binary classifier and is a reliable measure when dealing with imbalanced data. The area under the ROC curve (AUC) is a way to summarize its performance in a scalar value. AUC ranges between zero and one and indicates how well a classifier can separate between two classes, with closer to one indicating more accurate separation. We used AUC to evaluate the four models. Additionally, we reported F1-scores for each class, along with percent variance to illustrate individual class performance as well as general performance.

Results

The classification performances of the four models are shown in Table 2. Each was evaluated following the criteria of choosing the model with the highest AUC and with the lowest percent variance, as well as with high F1-scores for both classes. Based on these criteria, results from the best performing models are shown in bold, namely LR for Cody and SVM for Max.

Unfortunately, due to the low amount of data, it was not possible to create a model that was able to perform better than 71.4% on at least one subject, represented by the LR model of Cody's data. Max has two models with an AUC of 0.712, LR and SVM; however, the SVM model is chosen over the other due to the lower variance of 2.979%.

In general, the highest AUC will correlate with high F1-scores; however, it may not be indicative of acceptable performance for *both* classes. For example, looking at the results from the RF model for Cody, the AUC is higher than that of the SVM model due to the higher F1-score of 0.74 for the attentive class. Conversely, the F1-score for the inattentive class is 0.5, which is not accurate enough to be useful in practice. Model performance is specific to each subject since they were analyzed independently. Testing multiple models also proved advantageous since different models performed better for each subject.

Discussion

Overall, our findings indicated that E4 data are useful in categorizing states of attentiveness in children with ASD and extend the available literature by evaluating the predictive effectiveness of several algorithms when applied to RAI. Further, our findings suggest that a one size fits all approach may not be effective when selecting algorithms for use with physiological signals. The best performing model varied across participants, highlighting the need for individualization when

Table 2 – Performance outcomes are given for four different machine learning models								
	Cody				Max			
Model	Attentive F1-score	Inattentive F1-score	AUC	% Variance	Attentive F1-score	Inattentive F1-score	AUC	% Variance
LR	**0.74**	**0.69**	**0.714**	**6.060**	0.69	0.73	0.712	36.378
SVM	0.72	0.51	0.643	-5.007	**0.73**	**0.69**	**0.712**	**2.979**
RF	0.74	0.50	0.657	-3.547	0.70	0.40	0.596	-18.106
GBRT	0.71	0.43	0.614	-4.176	0.64	0.37	0.538	-24.464

processing a subject's physiological data as well as selecting classifying algorithms.

In the current investigation, we studied 12 features extracted from signals collected by the E4. This approach balances between extracting over 100 features [9] and studying a single feature [10],[20] and is grounded in years of study supporting that these 12 are significant to affective computing research applied to children with ASD [8],[12]. Further analysis, such as principal component analysis, could be used to test how much each feature impacts the classification metrics. The current offline analysis did not have to face bandwidth constraints that may arise with real-time transmission and processing of data; thus, reducing the number of signals collected and/or features extracted may be necessary as we move to real-time processing and closed-loop feedback during RAI. Therefore, ranking features will be part of our future work.

Challenges remain for collecting enough samples, and accurate samples, for the algorithms to learn more precise thresholds between one affective state and another. Since individually-designed models are often shown to outperform group-designed models, we would like to continue to collect data with these subjects. However, a limitation is the models trained for an individual can only assist that subject.

The algorithms were able to produce better-than-chance accuracy for our affective states of interest. Furthermore, the models have F1-scores > 0.67 for both classes; therefore, these models would match a human coder on predicting attentiveness or inattentiveness over two-thirds of the time. During future interventions, the models could be used by a robot to test a new sample of physiological data, return a prediction of affect (e.g., attentiveness or inattentiveness), and make a decision about actions to take during RAI. For example, if the model predicts the subject's signals indicate attentiveness, the robot can choose to continue with practicing a social skill. However, if the model predicts inattentiveness, the robot can remind the subject about the directions and about staying on task. The current investigation lays the groundwork for future research on the use of an affect-sensitive robot to develop social skills in learners with ASD.

Acknowledgments

The authors wish to acknowledge student researchers Janet Pulgares Soriano, Rebecca Castelly, Sabrina Daisey, Natalie Warning, Zen Kim, and Jacob Berdichevsky for their contributions to the research. We also want to thank the reliability coders from the College of Education and Human Development, the staff at the Norton Children's Autism Center, the subjects, and their families. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants included in the study. This research was supported by the National Science Foundation (NSF) under Smart and Connected Health (SCH) Grant #1838808 and REU Grant #1950137.

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For Further Reading

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