Developing Innovative Technology to Enhance Research and Practice in Individuals on the Autism Spectrum: A Computational Behavioral Science Approach

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Idaho Autism Summit
November 2, 2019
Boise, ID
Disclosures

Scientific Advisory Board Member

Affectiva, Inc.
Empatica, Inc.
Janssen Pharmaceuticals
Kanner & Asperger (1944)

5 Defining Characteristics of Autism:

1. Inability to relate in *the ordinary way* to people and to situations or to be encapsulated in an isolated world

2. Failure to use language appropriately

3. A fascination with objects rather than or more than with people

4. Good cognitive potentialities in some areas of functioning

5. An *anxiously* obsessive behavior pattern designed to maintain sameness, limiting spontaneity, and leading to rage or panic when external conditions do not meet the individual’s demands of the moment
Fig. 1. Characteristics of ASD that may contribute to emotion dysregulation.

Autonomic Arousal & ASD

• High rates of comorbidity with anxiety, fear, panic, and sensory processing disorders

• Increased vulnerability to stressors & limited ability to cope

• Maladaptive behaviors often associate with stressful events

• Atypical ANS responsivity to habituation, attentional, and social stimuli

Lydon, Healy, Reed, Hughes & Goodwin (2014). Developmental Neurorehabilitation
Woodard, Goodwin, Zelazo, Aube, Scrimgeour, Ostholthoff, & Brickley (2012). Research in Autism Spectrum Disorders
Goodwin, Groden et al. (2006). Focus on Autism and Other Developmental Disabilities
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Challenging Behaviors in ASD

- Stereotypical motor movements
- Aggression toward others
- Property destruction
- Self-injury
- Elopement
- Tantrums

30% of functional analysis of CBs are inconclusive when social and sensory functions are ruled out (Carr et al. 2007)
Knowledge & treatment options continue to lag for those with autism who are non-verbal, have an intellectual disability, and/or display challenging behaviors.

Under-represented in modern, large data repositories.

High throughput - unique setting to efficiently collect large amounts of standardized data and improve understanding of this understudied segment of the autism population.

Inpatient setting an ideal platform to identify mechanisms underlying emotional and behavioral symptoms to inform treatment.

Unique ability to study challenging behaviors in-situ due to safety of inpatient environment and control over environmental factors.

Biosensor Assessment of Stereotypical Motor Movements
Stereotyped and Repetitive Motor Mannerisms

Repetitive motor sequences that appear to the observer to be invariant in form and without any obvious eliciting stimulus or adaptive function.

- Hand flapping
- Body rocking
- Finger flicking
Strong need to develop substantially more efficient, objective, and accurate quantifiable measures of SMM in order to:

- better characterize movement features over time
- evaluate functional significance
- guide more personalized behavioral and/or pharmacological interventions
- document intervention outcomes
- compare/contrast across NDD populations with repetitive motor features (ASD, Lesch-Nyhan, Phelan-McDermid, Rett, Tourette, etc.)
- expand understanding of underlying pathophysiology

Albinali, Goodwin, & Intille (2012). *Pervasive and Mobile Computing*.


SMM and Cardiovascular Coupling

- N=10
- Lifeshirt measures of ECG and respiration
- RR intervals extracted, time-aligned with video annotations, resampled to 5Hz, and analyzed both as short sections defined by time and by SMM onsets and offsets

Characteristic response profile:

1. rapid cardiac acceleration prior to SMM
2. deceleration during SMM
3. slower acceleration post SMM
Predicting Imminent Aggression Onset in Minimally-Verbal Youth with Autism Spectrum Disorder using Preceding Physiological Signals

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Goodwin et al (2018). Pervasive Health ’18
Aggression to others may represent a maladaptive attempt to express or modulate physiological arousal due to distress.

In typical youth, greater ability to regulate physiological arousal is associated with fewer behavior problems.

Studies of disorders characterized by emotional and behavioral dysregulation such as bipolar disorder and antisocial behavior report a strong association between physiological disturbance and symptomatology.

Prior research demonstrates an association between physiological arousal and problem behavior in autism, wherein an individual may engage in aggression in an attempt to communicate or alleviate distress, and decrease or increase arousal to achieve autonomic equilibrium.

If these behaviors are punished or their function is not satisfied, physiological arousal can increase, exacerbating and perpetuating an escalating loop of distress, arousal, and aggression.
HYPOTHESIS & OBJECTIVE

Hypothesize that physiological arousal precedes aggressive behavior

Objective is to test whether proximal onset of aggression can be predicted from preceding physiological signals using wearable biosensors and machine learning algorithms
The following autonomic nervous system indices were recorded by the wrist-worn E4 biosensor to capture measures of peripheral physiological arousal:

- heart rate and heart rate variability, both derived from blood volume pulse (BVP) and inter-beat interval (IBI) via photoplethysmography at 64Hz
- electrodermal activity (EDA) at 4Hz
- Movement acceleration (ACC) using an embedded 3-axis accelerometer at 32Hz.
All 20 youth tolerated the E4 sensor after desensitization and usable data was obtained in all cases.

Inter-rater reliability for observed aggression onset and offset yielded 0.90 percent agreement and Cohen’s Kappa of 0.79.

69 independent naturalistic observational sessions were collected, totaling 87 hrs.

Out of 548 total aggressions observed with concurrent E4 data, mean and standard deviation of aggression frequency and duration was 27 (34) episodes in a four-hour period of 28 sec (32 sec) average length.

| Participant | P1  | P2  | P3  | P4  | P5  | P6  | P7  | P8  | P9  | P10 | P11 | P12 | P13 | P14 | P15 | P16 | P17 | P18 | P19 | P20 | Group | Mean | SD  |
|-------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Number of Sessions | 5   | 3   | 3   | 2   | 2   | 2   | 8   | 9   | 2   | 1   | 1   | 1   | 2   | 6   | 1   | 1   | 10  | 1   | 5   | 4   | 69   | 3.45 | 2.84 |
| Total Obs. Duration* | 9.33 | 3.97 | 3.77 | 3.02 | 1.25 | 0.57 | 7.02 | 8.47 | 2.72 | 1.43 | 0.22 | 1.38 | 1.6 | 8.47 | 0.52 | 1.02 | 20.48 | 0.78 | 5.1 | 5.87 | 86.99 | 4.35 | 4.80 |
| Number of Aggression Episodes | 72  | 7   | 13  | 8   | 9   | 6   | 35  | 30  | 50  | 1   | 2   | 3   | 9   | 39  | 1   | 8   | 130 | 2   | 76  | 47  | 548  | 27.40 | 33.84 |
| Mean Agg. Duration† | 9   | 102 | 77  | 11  | 19  | 9   | 19  | 19  | 18  | 50  | 3   | 1   | 15  | 19  | 6   | 51  | 7   | 103 | 4   | 7   | 22  | –   | 27.6 | 31.93 |

* Total observation durations are presented in hours. † Mean aggression durations are presented in seconds.
RESULTS
-Global & Person-Dependent Prediction Models-

ROC curves with 90% confidence intervals to predict onset of aggression in the upcoming minute, using all features from the past three minutes.

Solid line represents the global model.

Each curve with dashed lines represents one of the person-dependent models.
CONCLUSIONS

Proof-of-concept and feasibility linking observable aggressive behavior to preceding physiological signals

Approach moves the field of problem behavior assessment towards a new biologically-based, data-informed approach focused on prospective monitoring, prevention, and eventually real-time intervention

Begins to address a historically intractable problem for a segment of the autism population who is arguably the most in need of innovative approaches

Lays the groundwork for future work that defines and enables new opportunities for intervention before distress escalates to aggression
FUTURE DIRECTIONS

**More Advanced Analytics**

Test whether hybrid models improve prediction performance, i.e., global model iteratively updated to include the most significant physiological biomarker features from person-dependent models.

Explore ways to create more robust global prediction models by testing whether aggression onsets can be modeled as a nonhomogeneous Poisson process.

Evaluate whether regressing hazard rates from past observations can be performed through maximum likelihood estimation, leading to improved predictive performance across upcoming time ranges.

**Assistive Technology**

Push real-time aggression risk predictions via wifi or Bluetooth to a mobile phone, displaying a risk alert on the mobile application when indicated.

Caregivers monitor these alerts and initiate de-escalation or emotion regulation interventions before aggression occurs.

Assess effectiveness of these alerts facilitating de-escalation and/or emotion regulation interventions through a randomized controlled trial.
INHOME DATA CORPUS

PARTICIPANTS
• 20 FAMILIES W/ VARIETY OF BACKGROUNDS AND SES ACROSS MA AND RI.

• CHILDREN WITH ASD 4-14 YEARS OLD (M = 9, SD = 3), 4 FEMALE AND 16 MALE, RANGED FROM NON-VERBAL TO HIGH FUNCTIONING.

VIDEO
• 406 DAYS (M = 20, SD = 10) TOTALING 2,030 HOURS (M = 101, SD = 54) FROM 20 FAMILIES. 80% (SD = .05) FEATURED A PERSON OR MOTION IN THE SCENE.

Q SENSOR
• 203 DAYS (M = 14, SD = 4) TOTALING 299 HOURS (M = 21, SD = 15) FROM 14 FAMILIES. 75% OF EDA TRACINGS MET CRITERIA FOR VALID DATA.

AMI
• 116 NIGHTS (M = 8, SD = 5) OF SLEEP DATA FROM 12 FAMILIES.
Supervised Machine Learning = Human Annotate Behavior of Interest & Pattern Recognition to Characterize

Unsupervised Machine Learning = Pattern Recognition & Human Annotation to Characterize
ACKNOWLEDGMENTS

FAMILIES & PARTICIPANTS

SCIENTIFIC COLLABORATORS, STUDENTS, & ADMINISTRATIVE STAFF

Murat Akcakaya, Ph.D.  Carla Mazefsky, PH.D.
Fahd Albinali, Ph.D.  Ozan Özdenizci, M.A.
Catalina Cumpanasoiu, ABD  Christine Peura, M.A.
Deniz Erdoğmuş, Sc.D.  Susan Santangelo, Ph.D.
Yuan Guo, M.A.  Matthew Siegel, M.D.
Marzieh Haghghi, Ph.D.  Kahsi A. Smith, Ph.D.
James Heathers, Ph.D.  Amy Stedman, M.A.
Stephen Intille, Ph.D.  Qu Tang, ABD
Stratis Ioannidis, Sc.D.  Peng Tian, M.A.
  Mary Verdi, M.A.

FUNDING

Simons Foundation  National Institute on Deafness and Other Communication Disorders (P50 DC013027)
Nancy Lurie Marks Family Foundation  National Science Foundation (SCH-1622536, IIS-1118061)
Autism Speaks  Department of Defense Idea Development Award