

# Response Evaluation In Neuro fibromatos is Schwannomatos is INTERNATIONAL COLLABORATION

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# Digital biomarkers to support decentralized trials

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# Daily behaviors

There exists hidden behavioral patterns that can teach us about neurological disease

Facial expression

Communication

**Typing** 



Speech







Posture

Gaze patterns



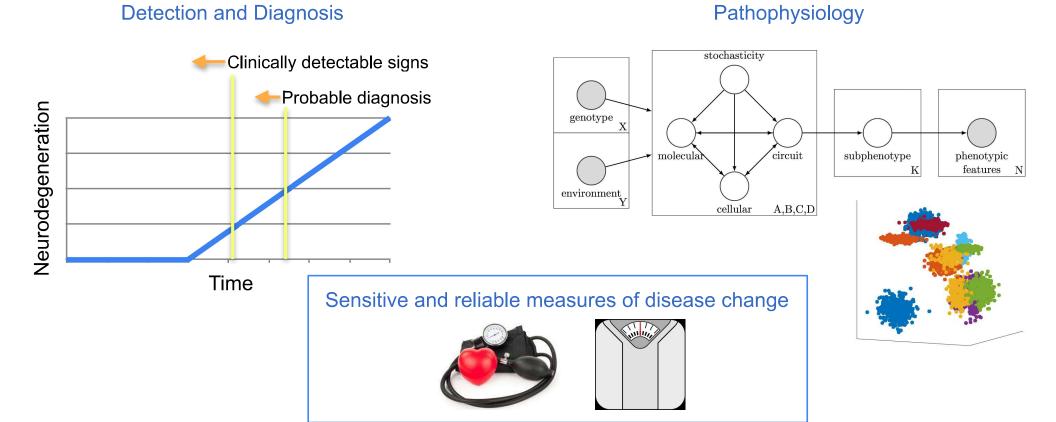


Reading

# Digital tools can capture behavioral patterns



# Clinical Utility of Identifying and Quantifying Patterns



# Digital Behavior Measurement Approaches

#### Active/Task-based Measurement

# neurobooth

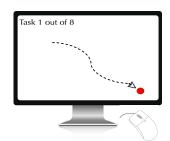






Can be remote:





#### Passive/Continuous Measurement



- Highly scalable
- Doesn't require consistently performed motor tasks
- Ecologically valid
- Potential for highly reliable measures

# Passage Reading

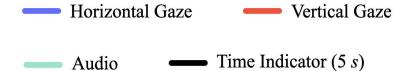


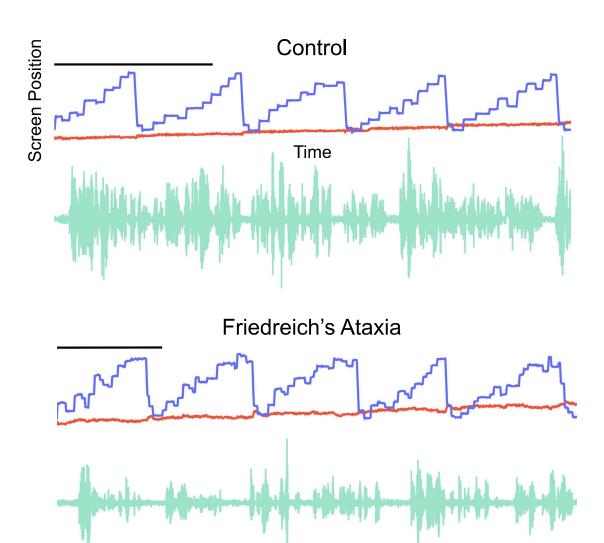






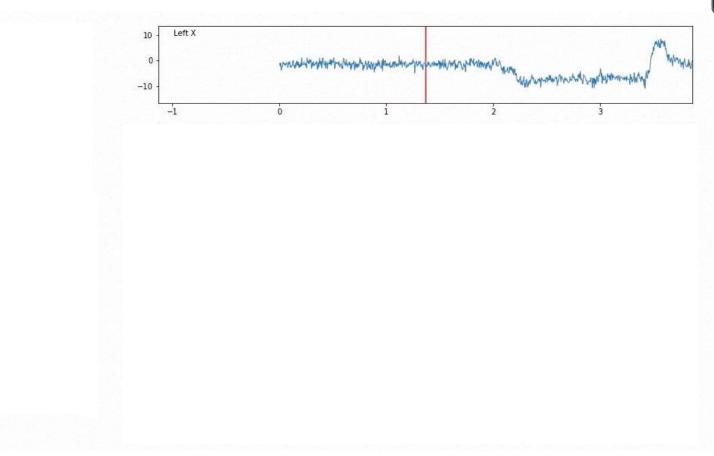
Bamboo walls are getting to be very popular. They are strong, easy to use, and good-looking. They provide a good background and can create a look of a Japanese garden. Bamboo is one of the largest and most rapidly growing grasses all over the world. Many varieties of bamboo are grown in Asia, although it is also grown in America. Last year we bought a new home and have been working on the flower garden. In a few more days, we will be done with the bamboo wall in our garden. We have really enjoyed the project.



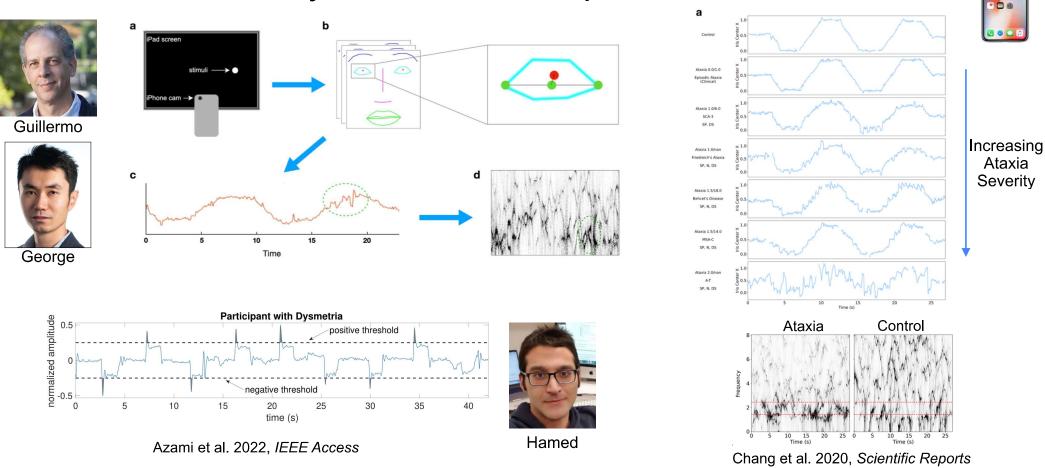


# Oculomotor analysis from mobile phone video

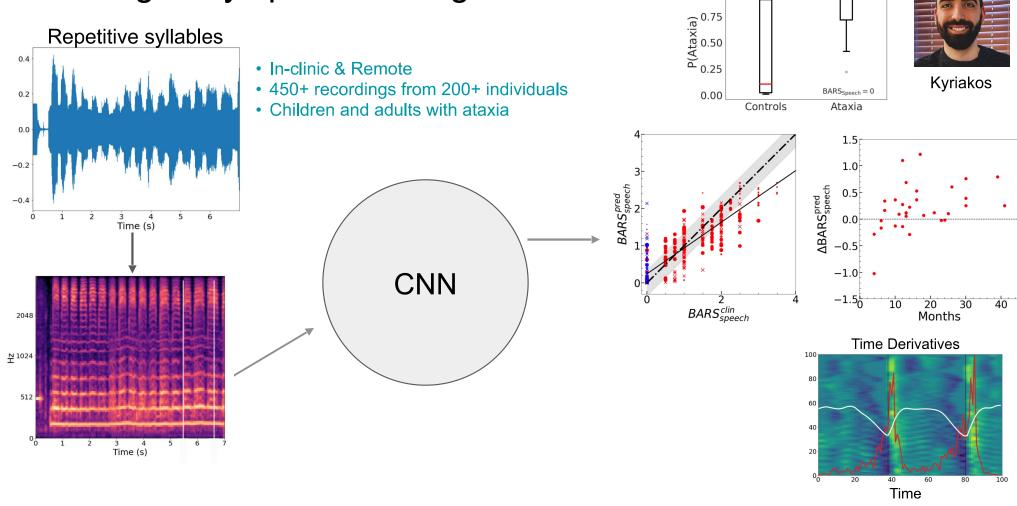




# Oculomotor analysis from mobile phone video



# Detecting early speech changes in ataxias

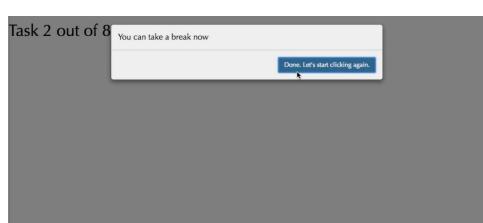


1.00

Vattis et al. 2023, medRxiv

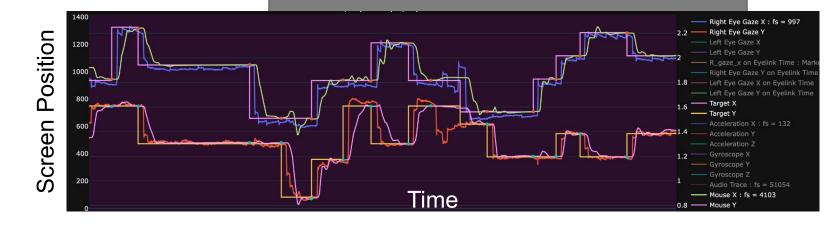
# Computer Mouse Task







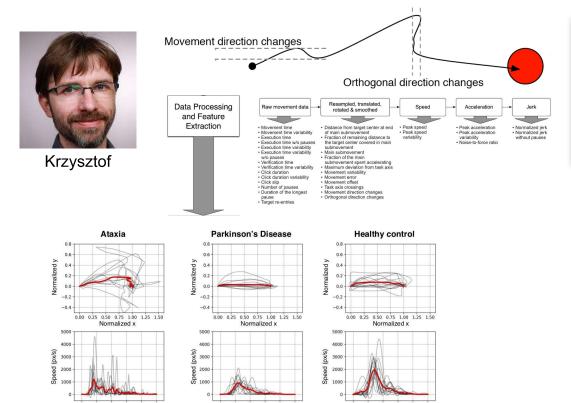
Krzysztof



# Web-based Computer mouse task





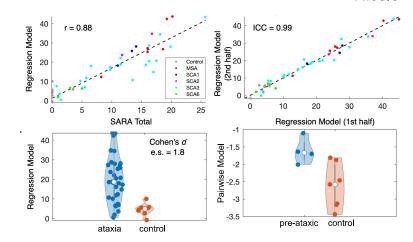


Gajos et al. 2020, Movement Disorders

Comparison (number in parentheses next to each class)	Number of features used	Sensitivity	Specificity	Positive predictive value	Negative predictive value
Parkinsonism (46) versus healthy (29)	5	0.913	1.000	1.000	0.879
Ataxia (95) versus healthy (29)	4	0.926	0.897	0.967	0.788
Mild ataxia (16) versus healthy (29)	6	0.750	0.966	0.923	0.875



Nicole



Eklund et al. 2023, Brain Communications

# Passive Motor Phenotyping with Wearable Sensors

In-Clinic — Task-based



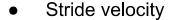


At-Home — Free-living



### Types of measurements from sensors worn at home

- Step counts, ambulatory time
- Activity counts, time in light/moderate/vigorous activity, sedentary time, energy expenditure

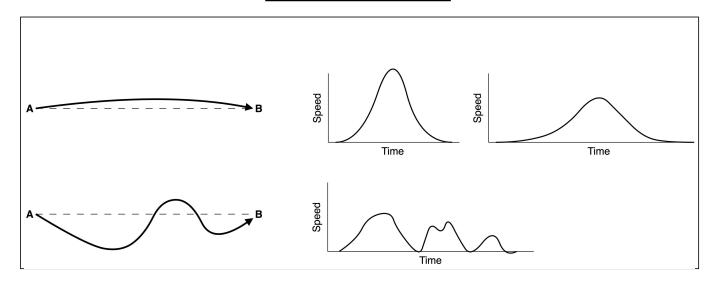


Acceleration time series statistics, power spectrum

Influenced by mood, fatigue, sleep quality, systemic illness, travel, device wear period

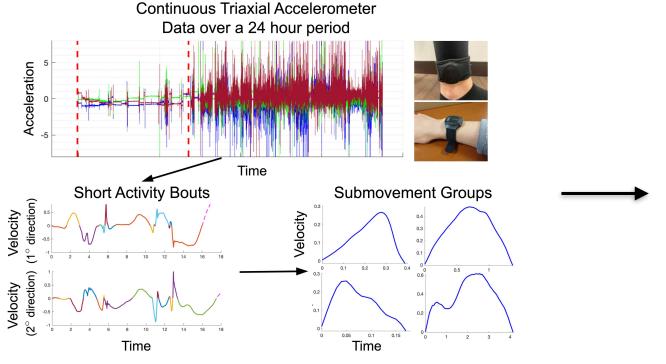
Can we create measures that are more specific for neurological disorders?

#### **Submovements**





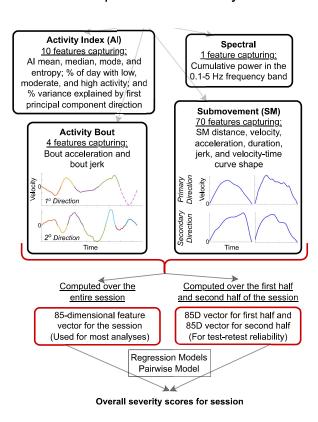
### Submovements from Natural Behavior



Gupta et al. 2022, *Cerebellum* - ataxia telangiectasia Eklund et al. 2023, *Brain Communications* - SCAs and MSA-C Gupta et al. 2023, *Nature Communications* - ALS \*Ongoing work in DRPLA, Friedreich's ataxia, UBTF

#### 85 Movement Features

- Individual feature analysis
- Composite model analysis

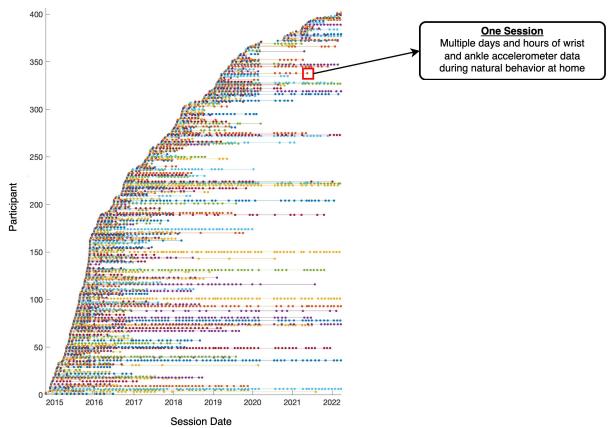


Amyotrophic Lateral Sclerosis (ALS)

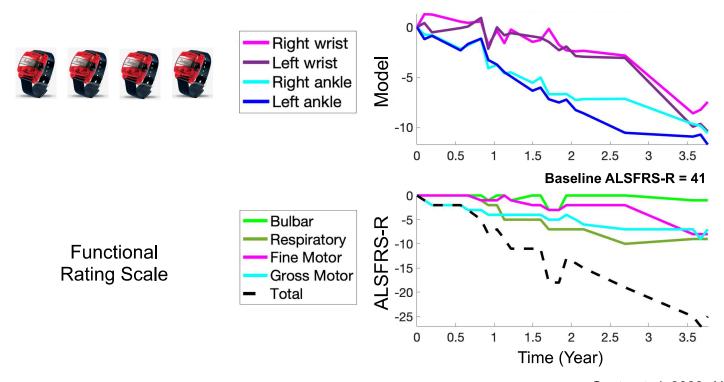
# Longitudinal ALS dataset

376 ALS, 26 controls (188 ALS, 6 controls with longitudinal data)



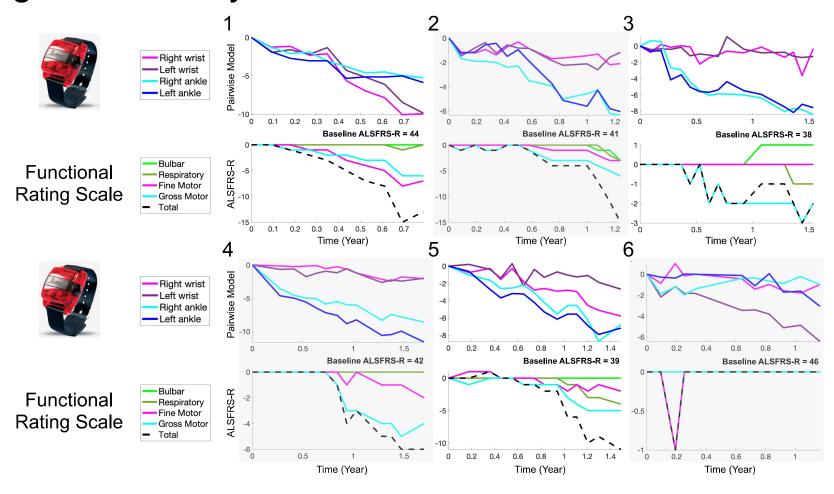


# Longitudinal analysis of ALS data: one individual



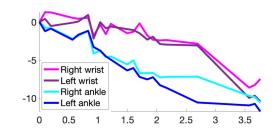
Gupta et al. 2023, Nature Communications

# Longitudinal analysis of ALS data: 6 individuals

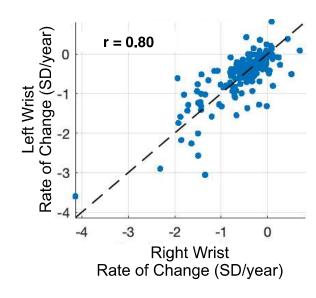


### Four Sensor Rate of Change Comparison

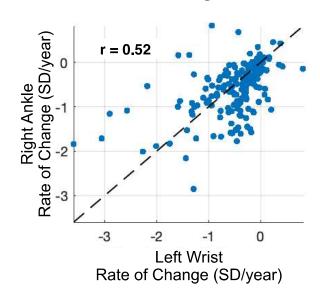
\* Each point represents an individual with ALS



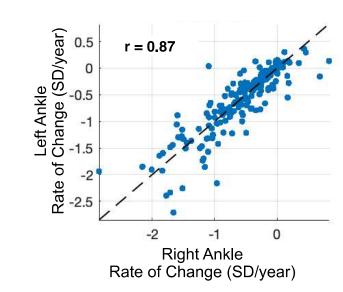
Left Wrist vs Right Wrist



Left Wrist vs Right Ankle



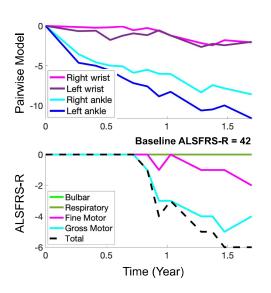
Left Ankle vs Right Ankle



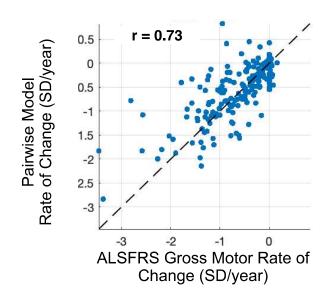
# What information does the ankle and wrist sensor capture?

\* Each point represents an individual with ALS

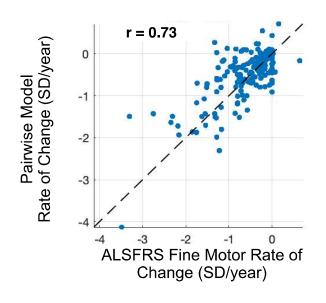
#### Individual Example



#### Ankle Captures Gross Motor Function

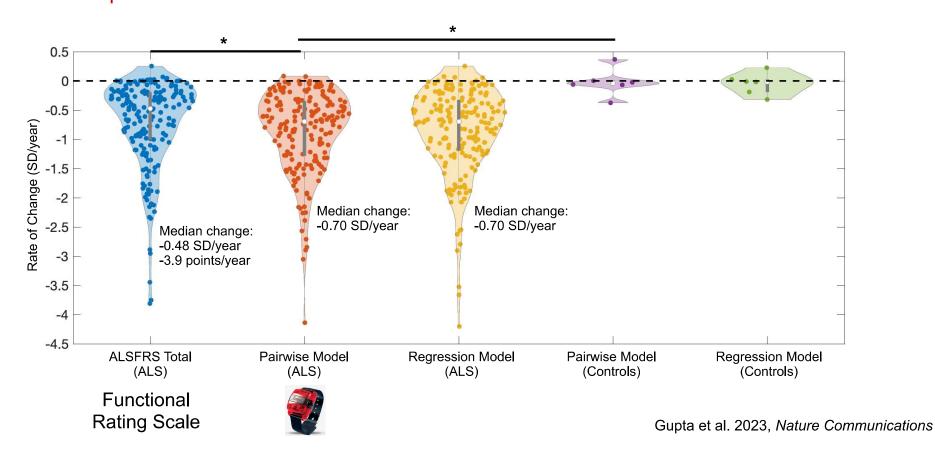


#### Wrist Captures Fine Motor Function



# Personalize By Taking Limb with Fastest Progression

\*Sample size estimates decrease from N=121 to N=76 with sensors-based outcome



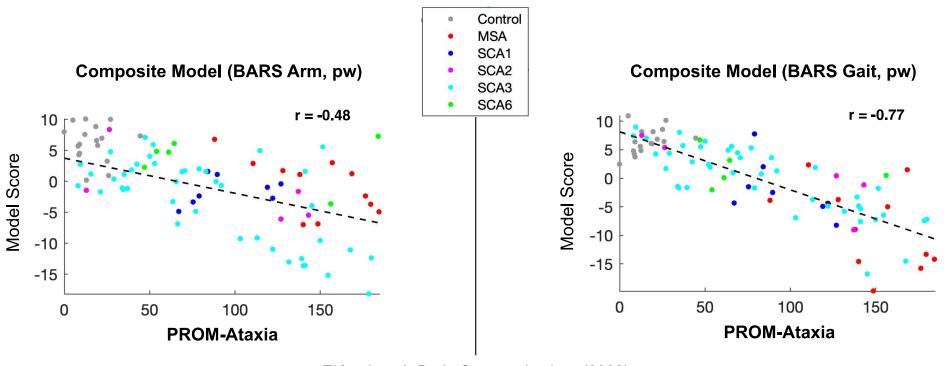
# Spinocerebellar ataxias (SCAs) and Multiple System Atrophy (MSA)



# Agreement with Patient-Reported Function



\* Each point represents a person



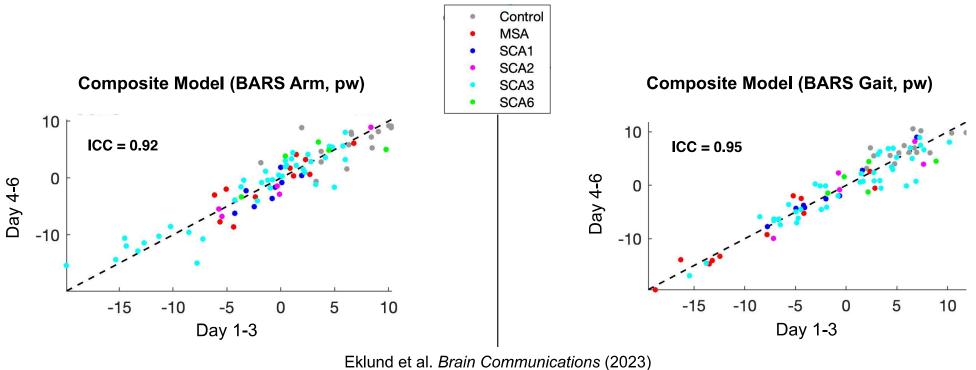
Eklund et al. Brain Communications (2023)



# Reliability within 1 week



\* Each point represents a person



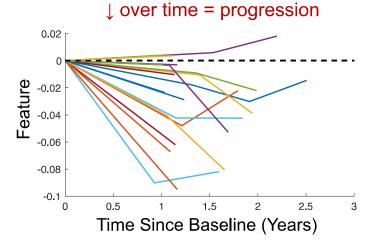
# Sensitivity to disease progression

12 SCA3, 2 SCA1, 1 SCA2, 1 SCA6, 3 MSA-C, 4 Controls (N = 23) SARA: 0.5-23 (10), Age: 30-70 (53), Sex(F/M): 10/9 6 preataxic individuals



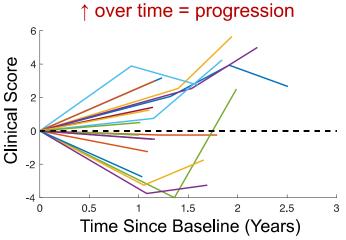
#### **Sensor Measure**

#### SM Distance; $\Delta$ from Baseline

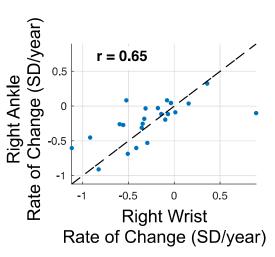


#### **Clinical Rating Scale**

### SARA Total; Δ from Baseline



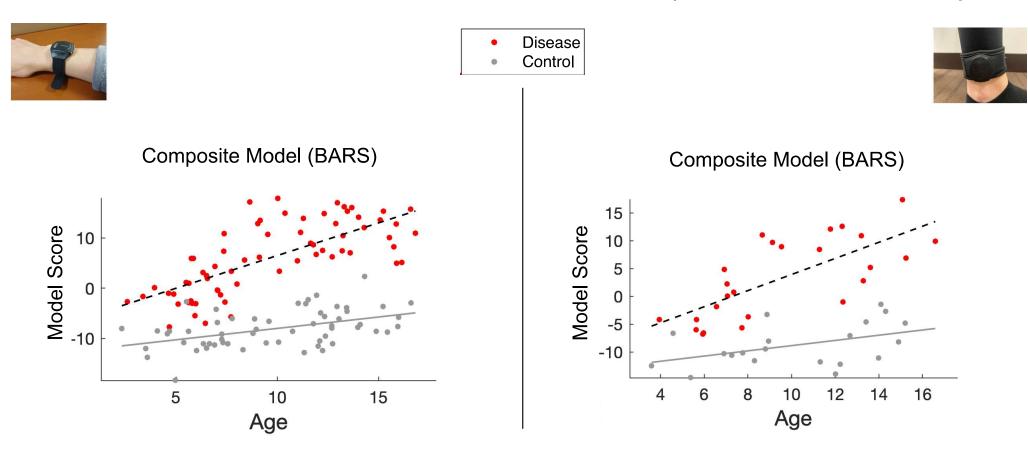
#### Right Wrist vs Right Ankle



# Pediatric Populations

Ataxia-Telangiectasia (A-T)
Friedreich's ataxia (FA)
Dentatorubral-pallidoluysian atrophy (DRPLA)
Upstream Binding Transcription Factor-related neurodegenerative disease (UBTF)

# Comparison with control participants (Children with A-T)

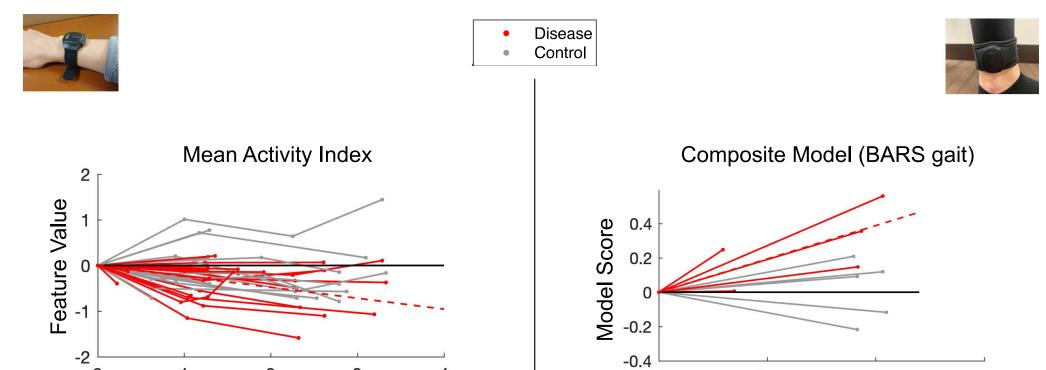


# Sensitivity to disease progression (Children with A-T)

3

Years from baseline

0



0.5

Years from baseline

0

1.5

### Summary

- There are a variety of digital technologies and behavioral assessment approaches
  - E.g., Eye movement, speech, fine motor function, gross motor function
- Active/task-based versus passive/task-free assessments of behavior
- Methods for analyzing natural behavior are maturing
- There is potential to translate digital technologies across populations
  - However the most rapidly changing measures are usually disease-specific
- Increasing utility to collect at-home digital measures in natural history studies

### Acknowledgements

#### **Research Group**

Present Anna Luddy Rohin Manohar **Brandon Oubre** Siddharth Patel Larry White Faye Yang Past Winnie China Mary Donovan Nicole Eklund Mainak Jas Nergis Khan Karin Knudson **Adonay Nunes** Jessey Ouillon Akansha Pandey **Kyriakos Vattis Andrew Chang** 

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# Discussion