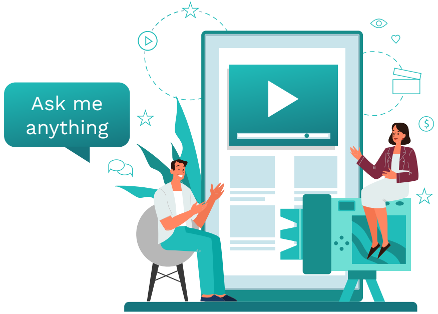
VIRTUAL JOURNAL CLUB



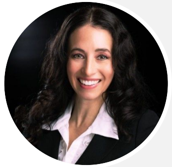
Advancing CNS care with digital measures of gait

DIGITAL MEDICINE SOCIETY

Thursday

August 7, 2025

11:00 am ET



Melissa Ceruolo
VP, Engineering and Biomarker Analytics
Medidata

Brett Meyer
Senior Data Scientist, Patient Experience
Medidata

Reed D. Gurchiek
Assistant Professor, Biomedical Engineering
Clemson University

Ryan McGinnis
Director, Center for Remote Health Monitoring & Associate Professor, Biomedical Engineering
Wake Forest University School of Medicine

Benjamin Vandendriessche
Chief Delivery Officer
Digital Medicine Society (DiMe)
Moderator

But first, housekeeping

- Today's session is being recorded
- To ask a question for discussion during Q&A, please:
    - Either 'raise your hand' in the participant window and moderator will unmute you to ask your question live, or
    - Type your question into the chat box
- Slides and recording will be available after today's session on DiMe's website.

V3+ is a modular evaluation process

Technical specification

Verification	**Changes to hardware/firmware?**	Evaluate and demonstrate the performance of a **sensor** within a sensor-based DHT (sDHT)
Usability validation	**Changes to use specification?**	Evaluate if an sDHT achieves specified goals with **ease**, **efficiency**, and **user-satisfaction**
Analytical validation	**Changes to software that change algorithm?**	Evaluate if an **algorithm** measures, detects, or predicts a physiological or behavioral measure
Clinical validation	**Expansion to a new patient population?**	Evaluate if an sDHT acceptably identifies, measures, or predicts a **meaningful** clinical, biological, physical, functional state or experience in the stated **context of use**

Clinical utility

Source: 1. NPJ Digital Medicine (s41746-020-0260-4) 2. V3+ framework

Validating Novel Digital Clinical Measures

DATAcc by DiMe

An evidence-based framework for rigorous **analytical validation** and selection of **reference measures** for both existing and novel digital clinical measures

Stage 1

Define objectives and gather initial data

Stage 2

Systematically identify the most rigorous reference measure(s)

- Identify existing reference measure(s)
- If necessary, consider developing novel comparator(s)
- If necessary, consider identifying anchor measure(s)

Stage 3

Design a rigorous analytical validation study

- Consider the impact of the data collection environment
- Conduct in-lab and/or in intended use environment analysis

Stage 4

Compile evidence to justify claims and support regulatory discussions

Source: 1. Project page 2. JMIR (e58956)

CORE MEASURES *of* PHYSICAL ACTIVITY

Digital Measures Development

DATAcc by DiMe

A **core set** of digital clinical measures applicable to the broadest range of therapeutic areas, making it easier to pick the right measure of **physical activity**

Ontologies

- Walking bout at specified bout durations
- Step count
- Walking speed
- Time spent in MVPA
- Measures of postural sway

Source: Physical Activity

Understanding the Central Nervous System (CNS) Burden

DATACC by DiME

Global Impact on Patients

3 Billion

people affected by neurological diseases globally[1]

Sponsor Burden in Alzheimer's

$370M **Average phase III AD trial cost[2]**

7.9yrs **Average trial duration for AD DMT trials[3]**

95% **Failure rate among drug candidates for AD[4]**

Trials Still Lack Patient Centricity

DATAcc by DiMe

~85% of clinical trials fail to retain enough patients[1]

30%
Average dropout rate across all clinical trials[1]

>66%
of sites fail to recruit a single patient[1]

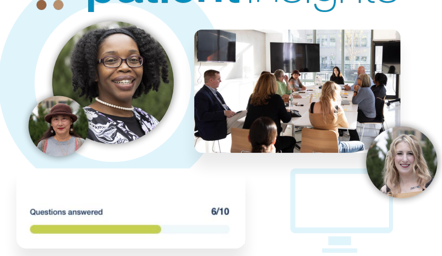
50%
of sites enroll one or no patients in their studies[1]

Innovation Through the Patient Lens

DATAcc by DiMe

Weaving patient and site-centricity from product to the experience level

patient insights



MEDIDATA

Medidata SiteTech Board

powered by SCRS

"Putting the patient first in an open and sustained engagement of the patient to respectfully and compassionately achieve the best experience and outcome for that person and their family."

Technologies developed with patient and site needs at the forefront

"If it's not site-friendly, it can't be patient-friendly - because if it doesn't work for the site, it won't be implemented as envisioned for the patient."

2132 IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING, VOL. 31, 2023

Chest-Based Wearables and Individualized Distributions for Assessing Postural Sway in Persons With Multiple Sclerosis

Brett M. Meyer, *Student Member, IEEE*, Jenna G. Cohen, Nicole Donahue, Samantha R. Fox, Aisling O'Leary, Anna J. Brown, Claire Leahy, Tyler VanDyk, Paolo DePetrillo, Melissa Ceruolo, Nick Cheney, Andrew J. Solomon, and Ryan S. McGinnis, *Senior Member, IEEE*

Analytical Validation

16 persons with multiple sclerosis (PwMS) performed a two-minute standing balance assessment on a force plate.

Chest located sensor offers similar relationships to force plate as previously used and validated sacrum sensor.

TABLE II

EYES OPEN POSTURAL SWAY FEATURE CORRELATION

	Chest & FP		Sacrum & FP		Chest & Sacrum	
Feature	r	p	r	p	r	p
Jerk	0.88	< 0.01	0.71	< 0.01	0.91	< 0.01
Dist	0.71	<0.01	0.74	< 0.01	0.58	0.02
RMS	-	-	-	-	-	-
Path	-	-	-	-	-	-
Range	0.60	0.01	0.74	< 0.01	0.94	< 0.01
MV	-	-	-	-	-	-
MF	0.78	< 0.01	-	-	-	-
Area	-	-	-	-	-	-
Pwr	-	-	-	-	-	-
F50	-	-	-	-	-	-
F95	-	-	-	-	-	-
CF	*0.44*	*0.09*	0.59	0.02	*0.43*	*0.10*
FD	0.62	0.01	0.63	0.01	0.51	0.04
ApEn	-	-	-	-	0.53	0.03
LyExp	-	-	-	-	-	-

Significant correlations of postural sway features amongst sensors and force platform (FP) comparisons. Results approaching significance ($0.05 < p < 0.10$) are italicized.

Individualized Distributions

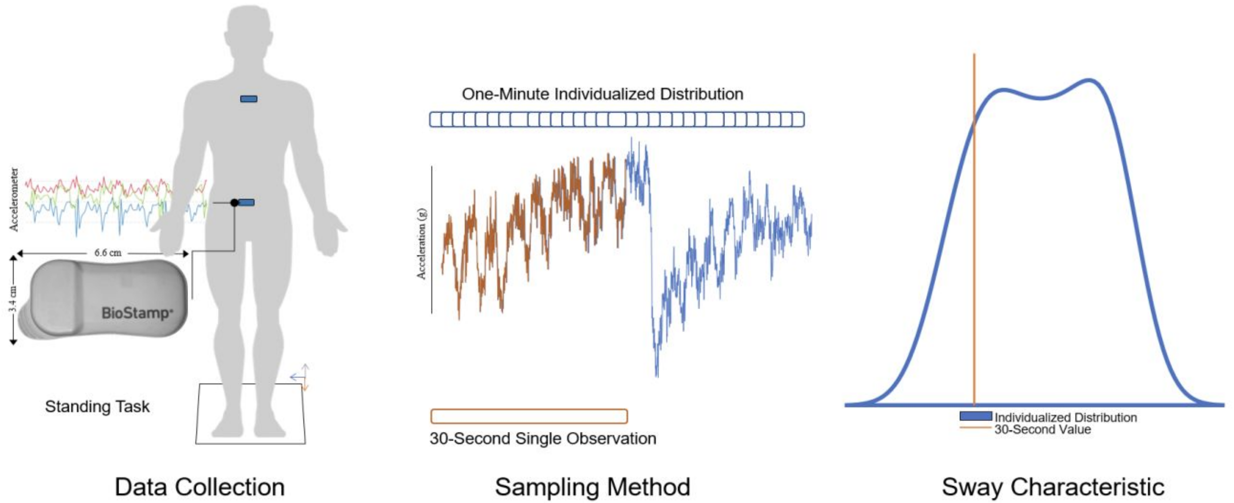


Fig. 1. Process overview of individualized distribution (ID) and a 30-second single observation (SO) methods. Data were collected using wearable sensors located on the chest and sacrum during various standing tasks. Features were computed using ID or SO method. The resulting feature displays the value of an example feature computed using the standard SO method on top of the distribution obtained from the ID method.

N = 39 PwMS

21:18 Faller:Non-Faller

12:27 Male:Female

51 ± 12 y/o

Two minute standing task

Clinical assessment: EDSS

PRO: ABC, MSWS-12, MFIS

Sway distributions increase strength of relationships to clinical outcomes

DATACC by DiME

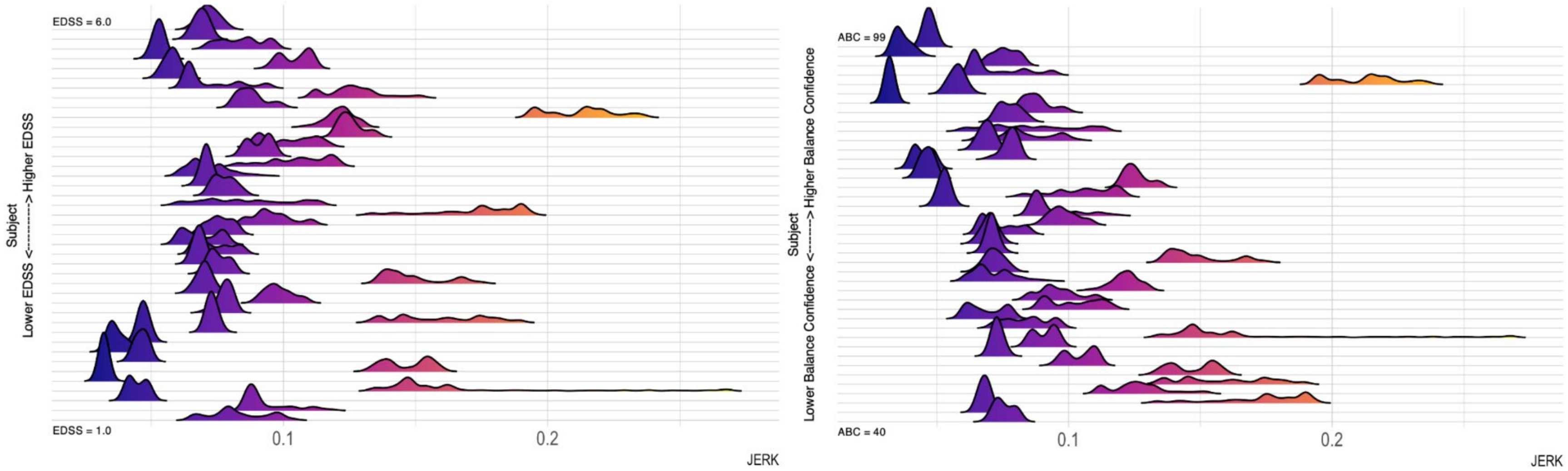
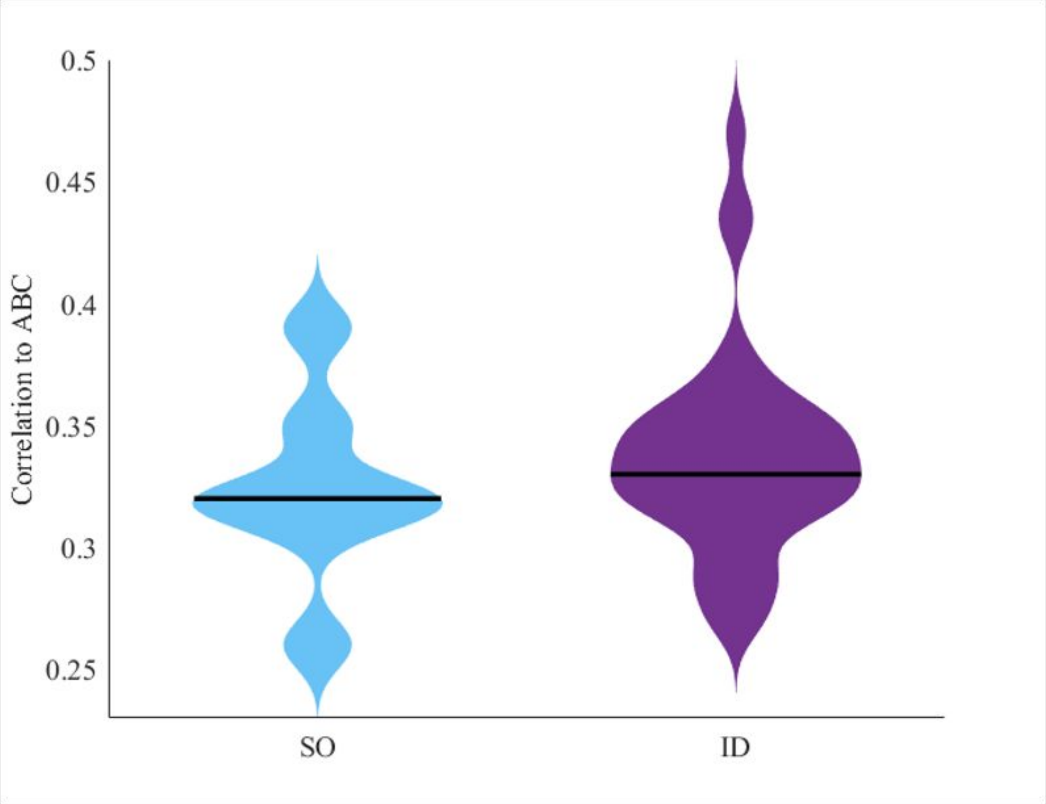


Fig. 5. Individualized distributions of Jerk found using the chest sensor data for the tandem standing task with subjects sorted in order of Expanded Disability Severity Score (EDSS) shown on the left and Activities Specific Balance Confidence Score (ABC) shown on the right. Higher EDSS and balance confidence subjects are at the top of the figures. The strongest correlations were 0.54 and 0.47 for EDSS and ABC with the 5th percentile.

Sway distributions increase strength of relations to PROs

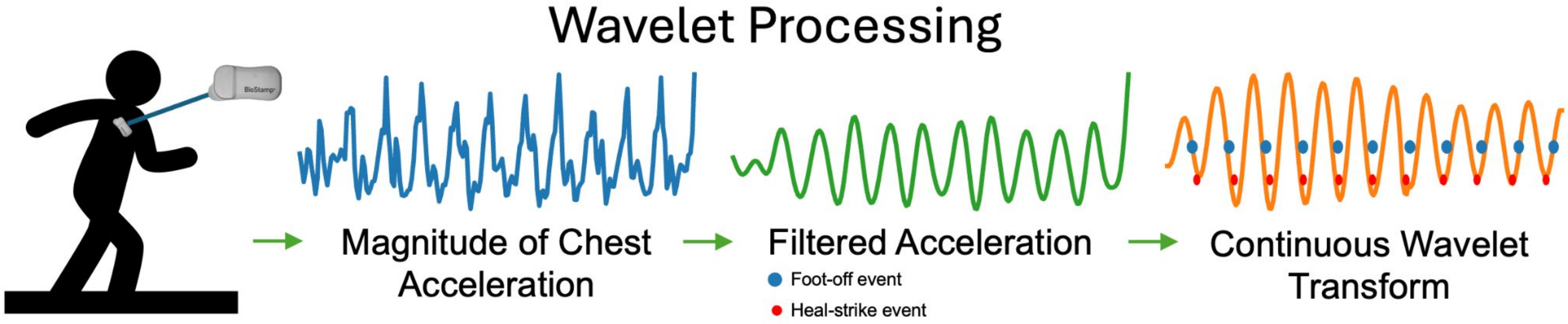


Accurate Gait Assessment and Reduced Patient Burden from a Chest-Mounted Accelerometer

Brett M. Meyer, *Member, IEEE* Reed D. Gurchiek, Ryan S. McGinnis, *Senior Member, IEEE* and Melissa Ceruolo

IEEE EMBC 2025 - Proceedings not yet published online

Methods



N = 10 Healthy Older Adults

Participants wore multiple Biostamp Sensors (including chest)

Participants completed nine ~20foot walks

N = 4 Persons with Huntington's Disease

VICON Motion Capture used for ground truth

Filtering and wavelet analysis to find stride events

Ref: Soltani et al. Algorithms for Walking Speed Estimation Using a Lower-Back-Worn Inertial Sensor: A Cross-Validation on Speed Ranges. 2021

Methods

- Acceleration calibrated to standing trial
  - Auto-calibration developed and leveraged for use in practice.
- Magnitude heavily filtered using altered ‘peak enhancement technique’ [1]
- Inspection of initial wavelet transform revealed heel contact events occured at zero-crossing and foot-off events occurred at signal valley.
- Optimization of wave and scale found with a grid search
- Right and Left stride segmented by medial-lateral acceleration

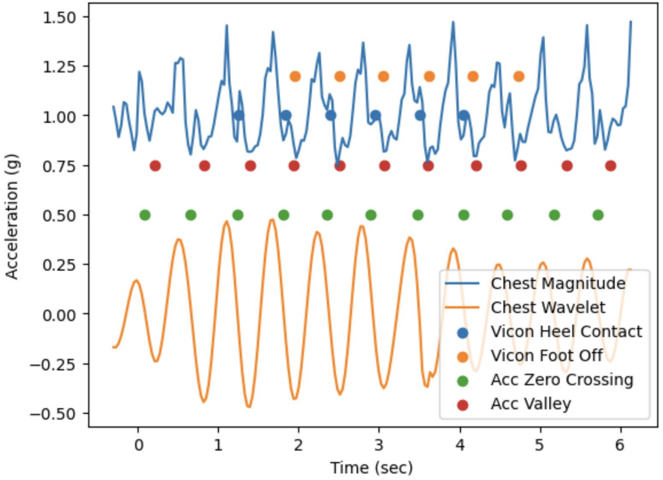


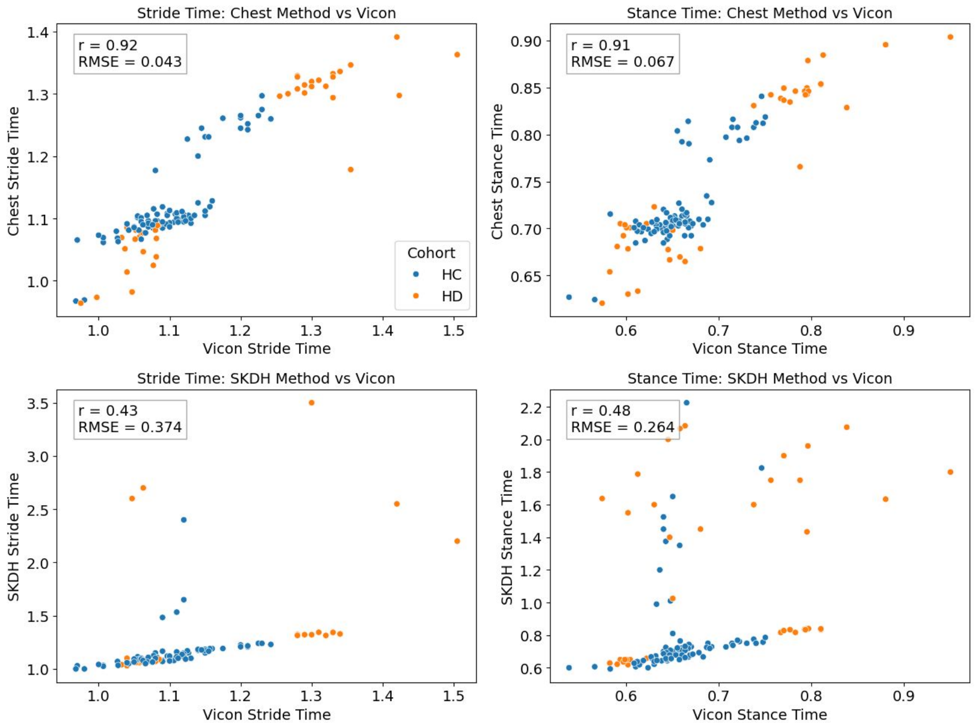
Figure 1. Walking trial with Vicon motion capture stride events (blue and orange dots) plotted over chest magnitude of acceleration (blue). Candidate heel contact (red) and foot off (green) events extracted from wavelet transformed signal

[1]: Soltani et al. Algorithms for Walking Speed Estimation Using a Lower-Back-Worn Inertial Sensor: A Cross-Validation on Speed Ranges. 2021

Analytical Validation and Comparison

DATAcc by DiMe

- Stride event information identified from 126 walks using VICON Motion Capture.
- Computation of stride time, stance time, % stance phase, and double support time.
- Comparison to Chest-scikit digital health (SKDH) performed with optimal parameters.
- Our proposed method vastly outperforms SKDH when considering the full set of walks.



Stride Length

- Deep learning model utilizes pretraining and transfer learning to find adequate performance from chest sensor.
  - Stride length estimation models from chest
    - Inverted Pendulum: error = 0.13 m
    - Deep learning model: error = 0.11 m
  - DL model offers lower patient and site burden due to lack of patient specific measurements at the expense of additional computation.

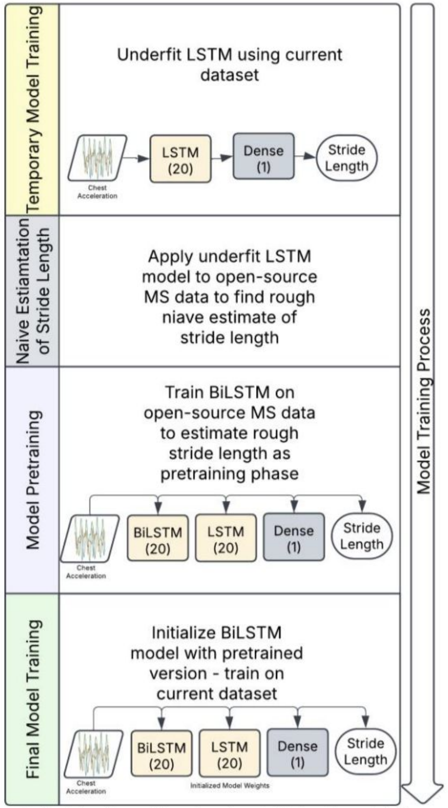


Figure 2. Training flow of deep learning stride length model. Temporary model trained on current healthy and Huntington cohort. Temporary model used to estimate stride length on unseen multiple sclerosis data (Naïve Estimation of Stride Length). Larger model pretrained on multiple sclerosis model. Final model initialized from the pretrained model and trained on current cohort.

IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING, VOL. 32, 2024 967

Assessing Free-Living Postural Sway in Persons With Multiple Sclerosis

Brett M. Meyer, *Graduate Student Member, IEEE*, Jenna G. Cohen, *Graduate Student Member, IEEE*, Paolo DePetrillo, Melissa Ceruolo, David Jangraw, Nick Cheney, Andrew J. Solomon, and Ryan S. McGinnis, *Senior Member, IEEE*

Passive Sway Analysis

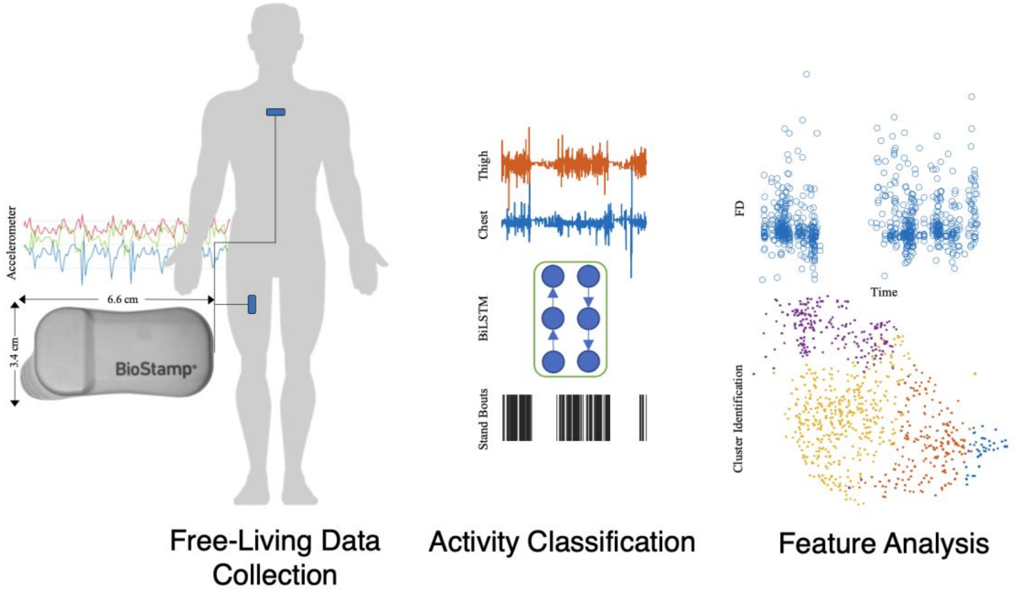


Fig. 1. Data processing overview. Free-living data collected from thigh and chest accelerometer and then classified using a deep learning classifier. Features of postural sway were computed for each standing bout as feature values vary throughout the day and clustering techniques were used to find similar data. BiLSTM: Bidirectional Long-Short-Term Memory network; FD: Frequency Dispersion.

N = 33 PwMS

16:17 Faller:Non-Faller

10:23 Male:Female

50 ± 12 y/o

48hr passive sensor wear

Clinical assessment: EDSS

PRO: ABC, MSWS-12, MFIS

Unique subsets of data exist in free-living sway

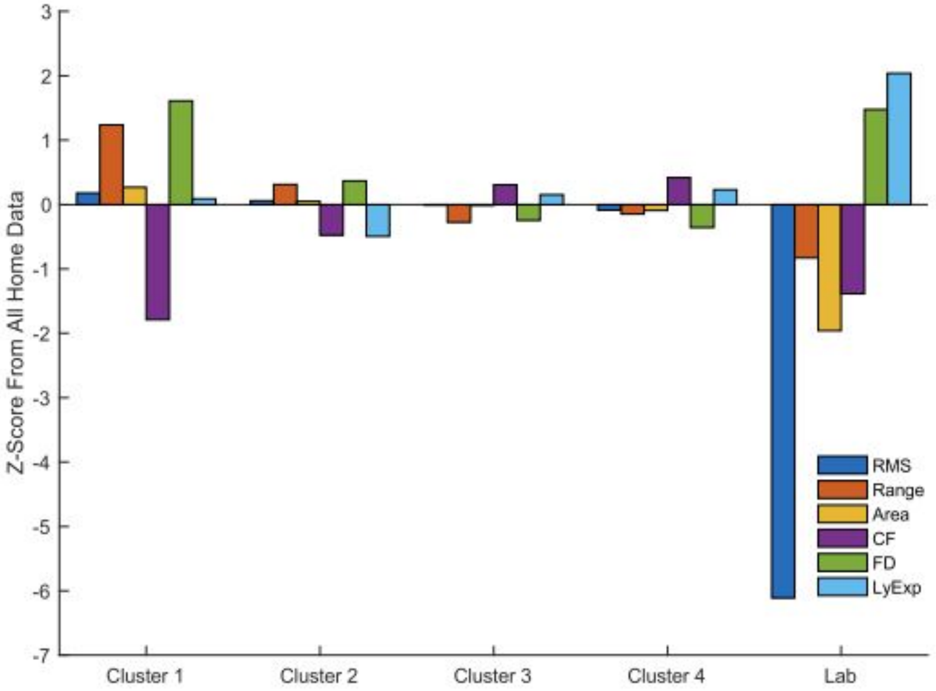


Fig. 4. Z-score differences for each feature between that derived from all remote data and that derived from clustered remote data or lab data.

Clusters demonstrate radically different relationships

Cluster 1
Aggregated Fall Classification Performance:
- 0.57 AUC, 60% accuracy, 0.63 F1

Strongest Correlation to ABC: -0.57 to CF
Strongest Correlation to EDSS: -0.38 to RMS

Cluster 2
Aggregated Fall Classification Performance:
- 0.71 AUC, 73% accuracy, 0.71 F1

Strongest Correlation to ABC: 0.64 to FD
Strongest Correlation to EDSS: -0.55 to FD

Cluster 3
Aggregated Fall Classification Performance:
- 0.53 AUC, 53% accuracy, 0.42 F1

Strongest Correlation to ABC: 0.42 to RMS
Strongest Correlation to EDSS: -0.61 to RMS

Cluster 4
Aggregated Fall Classification Performance:
- 0.16 AUC, 37% accuracy, 0.49 F1

Strongest Correlation to ABC: 0.22 to ABC
Strongest Correlation to EDSS: 0.17 (Area/CF)

COMMON MENTAL HEALTH DISORDERS

Digital Measures Development

Developing high-resolution, sensor-generated core digital measures that provide objective, scalable endpoints for common mental health disorders

Join us in transforming mental health research and care

THANK YOU

Melissa Ceruolo | Melissa.Ceruolo@3ds.com

Brett Meyer | Brett.Meyer@3ds.com

Reed Gurchiek | rgurchi@clemson.edu

Ryan McGinnis | rmcginni@wakehealth.edu

Ben Vandendriessche | ben@dimesociety.org

www.dimesociety.org

www.linkedin.com/company/dime-society

bit.ly/DiMe-Slack

DIGITAL MEDICINE SOCIETY