Recent advancements in digital assessment in ALS

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Wearable device and smartphone data quantify ALS progression and may provide novel outcome measures by Stephen A. Johnson, Marta Karas and others (*npj Digital Medicine*, 2023)

METHODS

- Analyzed the data of **40 people with ALS (PALS)**, followed for 6 months.
- Data collection via smartphone and wearable technology
  - (1) staff-administered ALSFRS-R via phone call;
  - (2) self-entry survey (ALSFRS-RSE, ROADS) via the Beiwe smartphone app;
  - (3) sensor data continuously collected via a wrist-worn **Insight Watch** by ActiGraph (N=20) or an ankle-worn **StepWatch** by Modus Health (N=20).

RESULTS

Figure 1. Very high correlation between ALSFRS-R (staff-administered) and ALSFRS-RSE (self-entry).

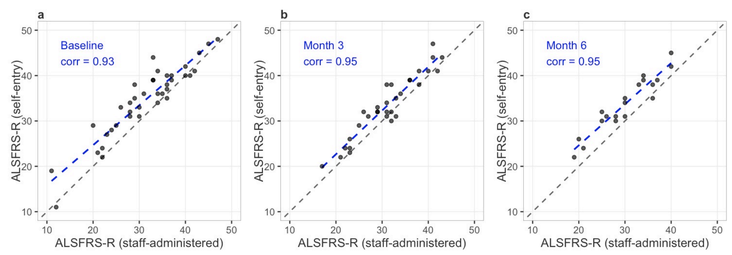
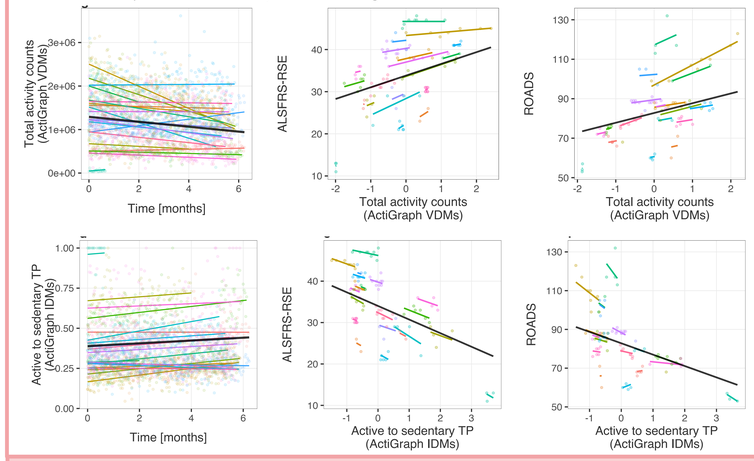


Figure 2. The following wearable PA daily measures showed both a **significant monthly decline** and **longitudinal association with both ALSFRS-RSE and ROADS scores**, as quantified with linear mixed-effects models (LMMs):

- ActiGraph vendor-provided (wear-filtered): total activity counts, non-sedentary time, steps, calories;
- ActiGraph investigator-derived: total activity counts, log(total activity counts), active-to-sedentary transition probability (TP), sedentary-to-active TP time, sedentary, non-sedentary time.

VDM – vendor-provided measure; IDM – investigator-derived measure.



CONCLUSION. In a functionally heterogeneous group of PALS, passively collected sensor data from wearable devices can characterize daily physical activity and its change over time.

Upper limb movements as digital biomarkers in people with ALS by Marcin Straczkiewicz and others (*eBioMedicine*, 2024)

METHODS

- Analyzed the data of **20 PALS**, followed for 6 months
  - (1) self-entry survey (ALSFRS-RSE) via the Beiwe smartphone app;
  - (2) sensor data continuously collected via a wrist-worn Insight Watch by ActiGraph.
- Developed daily **measures to quantify counts and duration of upper limb movements** (flexion, extension, supination, and probation) from raw accelerometer data from a wrist-worn sensor.

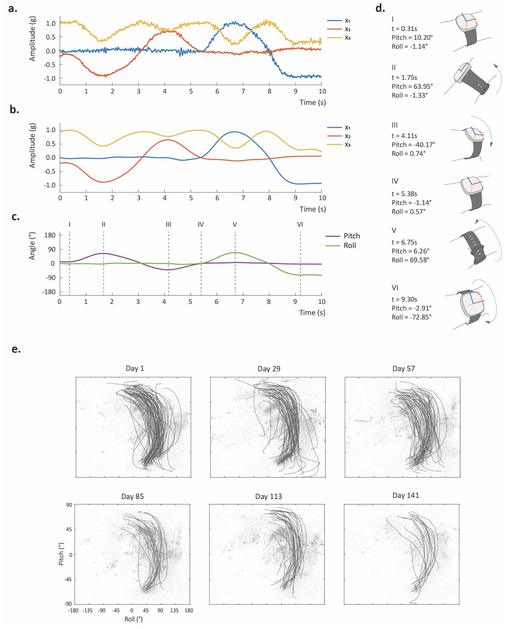
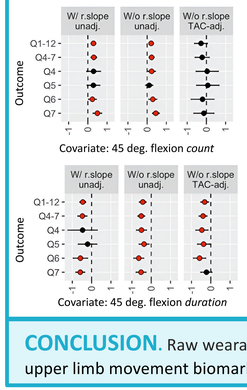


Figure 3. Calculation, interpretation, and application of forearm movement detection method.
(a): Wearable accelerometers collect data in three orthogonal axes.
(b): The data are smoothed using a low-pass filter.
(c): The smoothed data are transformed into pitch and roll angles.
(d): The angles indicate temporal sensor (forearm) orientation. Positions I-III depict forearm flexions and extensions, while positions IV-VI represent supination and pronation.
(e): Each black line corresponds to one forearm flexion by more than 90 deg. The patient performed 69, 52, 57, 20, 27, and 14 forearm flexions on observation days 1, 29, 57, 85, 113, and 141, indicating a decline in upper limb function.

RESULTS



- All count and duration daily measures for all four movements were **significantly associated with ALSFRS-RSE total score (Q1–12)** over time, as quantified with LMMs. The estimated slopes linked more frequent and faster limb movements to better physical function.
- Flexion and extension counts were significantly associated with Q6 and Q7. Supination and pronation counts were also associated with Q4. All duration metrics were associated with Q6 and Q7.
- **All duration measures retained their significance after adjusting for the Total Activity Counts** (TAC) daily measure.

Figure 4. Association between a daily upper limb movement measure (covariate; x-axis) and ALSFRS-RSE sub-score (outcome; y-axis), here showed for 2 measures. The vertical subplots correspond to different LMM formulas, with and without adjustment for TAC. In each LMM, outcome and covariate(s) were standardized. Q4 – handwriting, Q5 - cutting food , Q6 – dressing and hygiene, Q7 – adjusting bed clothes.

CONCLUSION. Raw wearable accelerometer data enabled the creation of interpretable digital upper limb movement biomarkers and monitoring of ALS progression in one's home environment.

Tracking ALS disease progression using passively collected smartphone sensor data by Marta Karas, Julia Olsen and others (*Annals of Clinical and Translational Neurology*, 2024+)

METHODS

- Analyzed the data of **63 PALS**, followed for up to 1 year.
- Data collection via the Beiwe smartphone app:
  - (1) active data: self-entry survey (ALSFRS-RSE);
  - (2) **passive data: smartphone sensor data (accelerometer and GPS)**, continuously collected.
- Derived daily measures from sensor data:
  - From GPS: time spent at home (hours), distance travelled (km);
  - From accelerometer data: walking measures, aggregates of minute-level Activity Index.
- Used LMMs to estimate baseline and monthly change in sensor data measures and their longitudinal associations with ALSFRS-RSE total score and sub-scores (Q1-3, Q4-6, Q7-9, Q10-12).

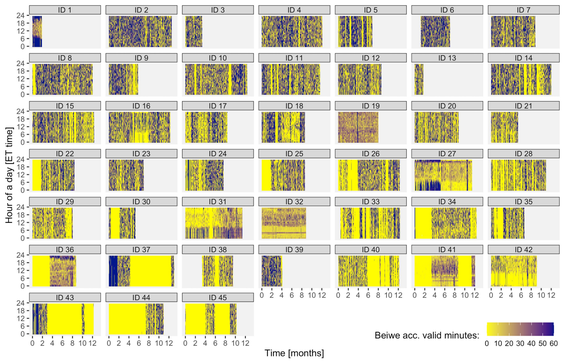


Figure 5. Analytic difficulty: varying patterns of missing smartphone accelerometer data between and within participants. Valid data minutes per hour are color-coded across hours of a day (y-axis) for each day of participant's monitoring period relative to the start date of monitoring (x-axis).

RESULTS

Table 1. **Col. 1**: measures derived from smartphone accelerometer and GPS data. **Col. 2-3**: average baseline and monthly change for a measure (estimated with LMMs with intercept and fixed-effect for time). **Col. 4**: average change in a measure associated with 1 point increase in ALSFRS-RSE total score (estimated with separate LMMs with intercept and fixed-effect for ALSFRS-RSE). Reported are effect estimates and (col. 3-4) associated p-values (note: in paper, BH correction is considered).

Daily measure (outcome in Models 1 and 2)	Baseline	Monthly change	Change for 1 point increase in ALSFRS-RSE
Home time [hours]	21.25	0.028 (0.401)	-0.076 (*0.015)
log(Distance travelled) [km]	2.061	-0.024 (0.114)	0.046 (*<0.001)
log(Activity Index)	6.154	-0.016 (0.206)	0.012 (0.264)
log(Activity Index from top 1 minute)	2.618	-0.015 (*0.041)	0.010 (0.183)
Walking cadence [steps/s]	1.746	-0.001 (0.364)	0.003 (*0.030)
Walking cadence [steps/s] from top 1 minute	1.885	-0.004 (0.084)	0.007 (*0.001)
log(Step count)	3.460	-0.090 (*0.020)	0.126 (*0.002)
log(Step count from top 1 minute)	2.496	-0.056 (*0.043)	0.085 (*<0.001)

CONCLUSION. Smartphone sensors can unobtrusively track physical activity and mobility in PALS, potentially aiding disease monitoring and future research.

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