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Activity Fragmentation and Posture-Transition Structure in Adults Aged 70-95 Years: A Participant-Level Analysis of HAR70+

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Research Article

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Movement Fragmentation and Posture-Transition Structure in Adults Aged 70–95 Years: A Secondary Analysis of HAR70+

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Abstract

Background: Accelerometer summaries of older adults commonly emphasize accumulated activity and sedentary time, but these totals do not show how movement is distributed into bouts or how often posture and locomotor states change. We examined whether movement amount, continuity, and state organization provide distinct participant-level descriptions in HAR70+. **Methods:** This secondary analysis used synchronized lower-back and thigh accelerometry with validated second-by-second activity labels from 18 adults aged 70–95 years during approximately 40 minutes of semi-structured activity per participant. Labels were grouped as ambulatory activity (walking, shuffling, and stair ascent or descent), standing, sitting, or lying. We calculated activity composition, transition density, normalized state entropy, median active-bout duration, and longest inactive bout for each participant. Participant-level means and 95% bootstrap confidence intervals were estimated with 5,000 resamples. Spearman correlations examined ambulatory time in relation to transition density and state entropy. **Results:** The recordings comprised 12.55 hours. Mean ambulatory time was 51.05% (95% CI 47.00–54.55), while sitting and lying occupied 30.53% (27.29–34.31).

Participants made 4.60 state transitions per minute (4.02–5.23), and normalized state entropy averaged 0.669 (0.650–0.688). The participant-level mean of median active-bout duration was 2.68 s, whereas the longest sitting-or-lying bout averaged 4.87 min. Ambulatory time was weakly related to transition density (Spearman $\rho = -0.220$, $p = 0.381$). Its relationship with state entropy was negative but imprecisely estimated ($\rho = -0.447$, $p = 0.063$). **Conclusions:** Movement amount, bout continuity, and state-transition organization captured different properties of the HAR70+ sequences. These protocol-bound results support explicit reporting of temporal organization in older-adult wearable measurement studies, but they do not estimate habitual behavior or establish clinical meaning.

Keywords: accelerometry; older adults; activity fragmentation; posture transitions; sedentary behavior; HAR70+

1 Background

Physical activity and sedentary behavior are established components of healthy ageing, yet the way movement is organized across time may carry information that accumulated duration alone cannot provide. Conventional accelerometer summaries reduce a complex activity sequence to minutes spent active, sedentary, or in selected intensity bands. This compression is useful for surveillance, but it treats a sustained 20-minute walk and twenty one-minute walks as equivalent even though the underlying movement patterns differ. In later life, frequent interruption, short bouts, and prolonged inactive periods may reflect constraints in endurance, confidence, mobility, environmental opportunity, or task organization. For this reason, activity fragmentation has emerged as a complementary descriptive phenotype rather than a replacement for total activity volume (Wanigatunga et al., 2019a,b).

The interpretation of wearable-derived movement metrics in older adults requires particular care. Device placement, activity definitions, monitoring context, and preprocessing choices can materially change estimates (Schrack et al., 2016; Pruitt et al., 2008). A label such as

"sedentary" also carries a postural and contextual meaning that cannot always be inferred from acceleration intensity alone; terminology consensus distinguishes sedentary behavior from physical inactivity (Tremblay et al., 2017). Validation datasets with explicit posture and locomotion labels therefore remain valuable, even when their recordings are shorter and more structured than population monitoring. They allow the temporal properties of a labeled activity stream to be examined directly and reproducibly.

HAR70+ was developed to support activity-type recognition in adults aged 70 years and older. The dataset includes synchronized lower-back and thigh accelerometry and manually validated activity labels for walking, shuffling, stair movement, standing, sitting, and lying (Ustad et al., 2023b,a). It is unusual in covering participants up to 95 years of age and in preserving transitions between common activities. Previous use of the resource has emphasized classification. A participant-level analysis of the labeled sequence can instead ask a different question: what aspects of movement organization are observable within the benchmark itself?

We therefore quantified three related but non-identical domains: composition (the proportion of recording time in each state), continuity (bout-duration summaries), and organization (transition density and state entropy). We also examined whether participants with more ambulatory time necessarily changed states more often or occupied a more diverse state distribution. This distinction is relevant beyond the original data-collection region because wearable studies of older adults require transparent choices about the unit of inference, state taxonomy, and monitoring context. The analysis was deliberately descriptive. Because HAR70+ contains approximately 40 minutes of semi-structured activity per participant, we did not treat the recordings as estimates of habitual daily behavior, mobility disability, or future health risk.

2 Methods

2.1 Study design and data source

We conducted a secondary analysis of the public HAR70+ dataset, distributed through the UCI Machine Learning Repository (DOI: 10.24432/C5CW3D) (Ustad et al., 2023a). The source dataset contains data from 18 adults aged 70–95 years who wore accelerometers on the lower back and thigh during a semi-structured protocol. The sensors were sampled at 50 Hz. The present analysis used the provided validated activity label associated with each sample; it did not retrain or modify the original activity-recognition model.

The unit of inference was the participant. High-frequency samples within a participant were used to reconstruct labeled bouts, but uncertainty summaries were calculated across participants. This distinction avoids treating millions of sensor samples as independent observations.

2.2 Activity definitions

The seven retained labels were walking, shuffling, stair ascent, stair descent, standing, sitting, and lying. Walking, shuffling, and both stair categories were designated as ambulatory activity. Sitting and lying were combined only for the inactive-bout summaries; their individual proportions were retained. Standing was kept separate because it is neither ambulatory nor equivalent to sitting or lying.

For each participant, activity composition was calculated as the number of samples in a state divided by the participant's total labeled samples. Contiguous samples carrying the same label were collapsed into a bout. Bout duration was the number of samples in that run divided by 50 Hz. A transition occurred whenever consecutive samples had different labels.

2.3 Fragmentation and organization measures

Transition density was defined as the number of label changes divided by valid recording minutes. It describes the frequency of observed state changes, without asserting whether a higher value is beneficial or adverse. Median active-bout duration summarized the typical duration of contiguous ambulatory runs. The longest inactive bout was the maximum duration of any contiguous sitting or lying run.

State diversity was described using normalized Shannon entropy. If p_k denotes the proportion of a participant's recording assigned to state k, entropy was calculated as

$$H = -\frac{\sum_{k:p_k>0} p_k \log(p_k)}{\log(K)}, \tag{1}$$

where $K = 7$. The measure approaches zero when one state dominates and approaches one when time is evenly distributed across all states. Entropy depends on protocol coverage and should not be interpreted as a clinical score.

2.4 Statistical analysis

Participant-level means were accompanied by percentile 95% confidence intervals obtained from 5,000 nonparametric bootstrap samples of participants. Medians and interquartile ranges were retained in the machine-readable tables. Spearman rank correlations assessed the association of ambulatory-time percentage with transition density and normalized entropy. Correlations were treated as exploratory, and exact two-sided p values are reported without dichotomizing them into "significant" and "non-significant" findings. Analyses were implemented in Python 3.12 using pandas, NumPy, SciPy, and Matplotlib. The fixed random seed was 20260830. Figure 1 summarizes the analysis sequence.

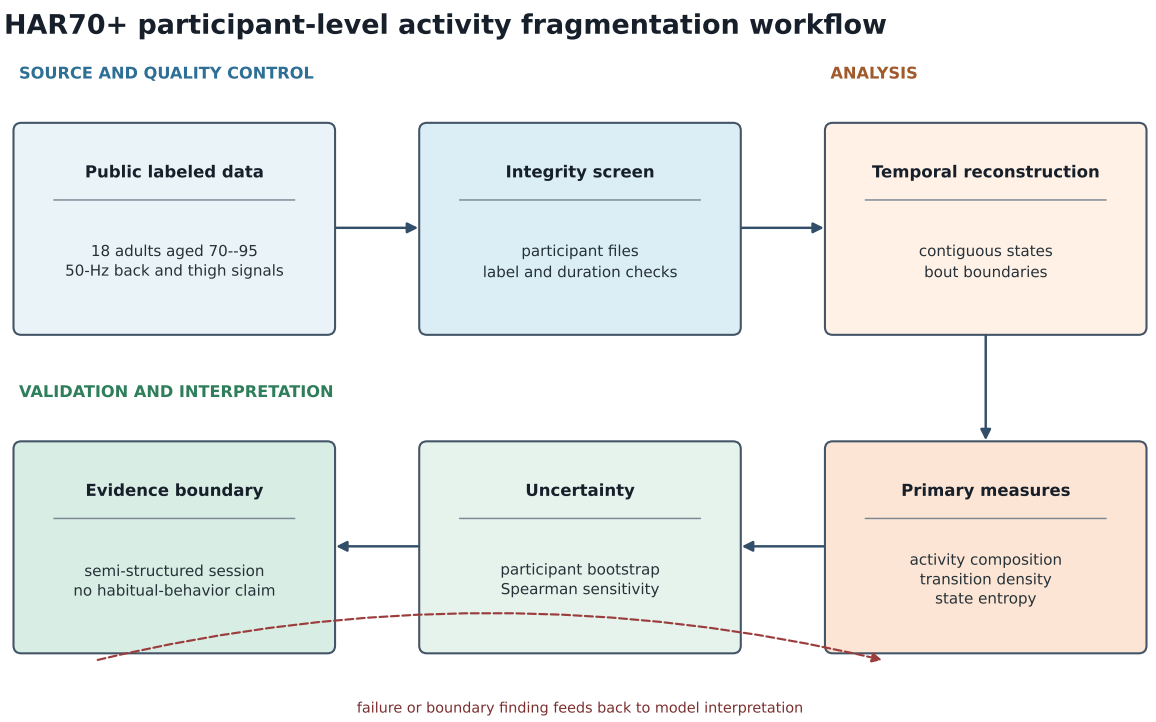


Figure 1: Analysis workflow. High-frequency labeled sensor records were converted to participant-level composition, bout, and transition measures before descriptive uncertainty estimation. The evidence boundary distinguishes a semi-structured benchmark from habitual free-living monitoring.

3 Results

3.1 Recording coverage and activity composition

All 18 participants contributed analyzable records, totaling 12.553 hours. Mean recording duration was 41.84 min (95% CI 39.22–44.34), with a median of 41.05 min and an interquartile range of 5.68 min. Walking was the largest single category, occupying a mean 47.73% of the recording. Shuffling contributed 2.90%; stair ascent and descent each accounted for about 0.2%. Standing occupied 18.41%, sitting 21.39%, and lying 9.14%.

Combining the four ambulatory labels, participants spent a mean 51.05% of recorded time in ambulatory activity (95% CI 47.00–54.55). Sitting and lying together occupied 30.53% (27.29–34.31). These percentages describe the composition of the study protocol and cannot be converted into daily activity prevalence.

Table 1: Participant-level activity and fragmentation summaries ($n = 18$).

Measure	Mean	95% CI	Median	IQR
Recording duration (min)	41.84	39.22–44.34	41.05	5.68
Ambulatory activity (%)	51.05	47.00–54.55	51.24	8.06
Sitting plus lying (%)	30.53	27.29–34.31	29.55	9.61
Transitions per minute	4.60	4.02–5.23	4.59	2.41
Normalized state entropy	0.669	0.650–0.688	0.672	0.064
Median active bout (s)	2.68	2.17–3.32	2.22	1.24
Longest inactive bout (min)	4.87	4.18–5.61	4.72	2.04

3.2 Bout continuity and transition structure

The participant-level mean of median active-bout duration was 2.68 s (95% CI 2.17–3.32), indicating that the labeled ambulatory sequence was highly segmented at the temporal resolution of the annotations. The longest sitting-or-lying bout averaged 4.87 min (4.18–5.61). Participants changed labeled state 4.60 times per minute (4.02–5.23). Normalized state entropy averaged 0.669 (0.650–0.688), showing that the protocol exposed participants to multiple states while retaining unequal time allocation.

Ambulatory-time percentage was weakly and inversely associated with transition density ($\rho = -0.220$, $p = 0.381$). Its association with entropy was more negative but remained imprecisely estimated ($\rho = -0.447$, $p = 0.063$). Thus, participants who accumulated more ambulatory time did not necessarily make more frequent transitions or distribute their time more evenly across labels. Figure 2 presents the activity composition, participant-level fragmentation relationship, and bout-duration distributions.

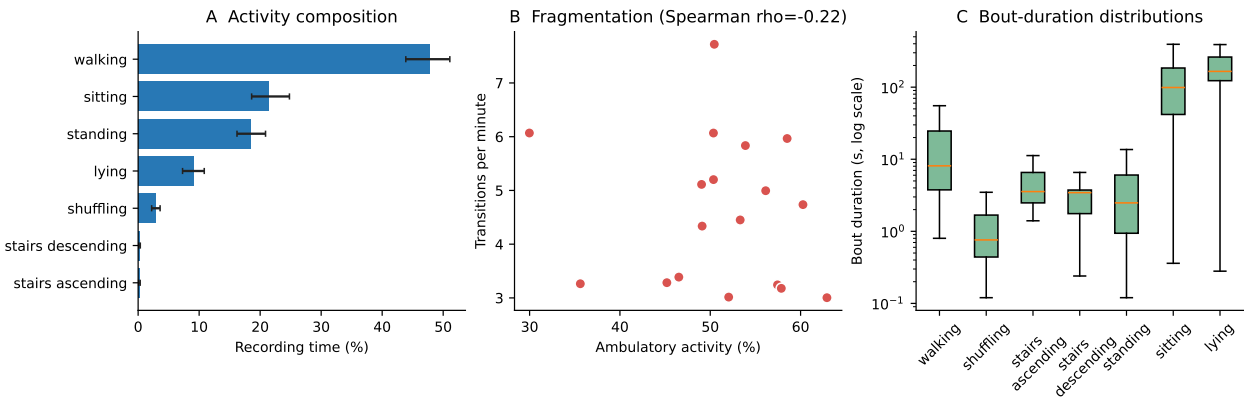


Figure 2: Activity composition and temporal structure in HAR70+. Error bars in panel A are participant-bootstrap 95% confidence intervals. Panel B uses one point per participant. Panel C shows labeled bout durations on a logarithmic scale; outliers are suppressed in the boxplot display but retained in all calculations.

4 Discussion

This participant-level analysis separates three features that are often collapsed in wearable summaries: how much time was spent moving, how continuous that movement was, and how the labeled states were organized. Within HAR70+, ambulatory activity occupied about half of the protocol, yet the typical labeled active bout was only a few seconds and participants changed states more than four times per minute. The absence of a clear positive relationship between ambulatory time and transition density illustrates why total activity and fragmentation should not be treated as interchangeable measures.

The short active bouts are partly a property of the semi-structured protocol and annotation process. Participants were asked to perform multiple activities in a limited period, and fine-grained labels divide locomotion into walking, shuffling, and stair categories. Consequently, a change from walking to stair ascent counts as a transition even though both states are ambulatory. This is not a defect in the dataset, but it defines the estimand. The resulting metrics describe label-sequence organization under the HAR70+ protocol, not spontaneous fragmentation across an ordinary day.

The analysis nevertheless has methodological value. First, it makes the participant the unit of uncertainty, preventing high-frequency samples from creating misleadingly narrow

confidence intervals. Second, it shows how a validation dataset can support sequence-level characterization in addition to classifier benchmarking. Third, it exposes the sensitivity of fragmentation measures to state taxonomy. A binary active/inactive sequence would yield different transition rates and entropy values from the seven-state sequence used here. Future benchmarking should therefore report the state map alongside any fragmentation metric.

Population studies have linked fragmented activity with ageing and adverse outcomes (Wanigatunga et al., 2019a,b), while prolonged sedentary accumulation has been associated with health risk (Diaz et al., 2017). Those findings do not transfer directly to HAR70+. The present sample is small, the observation window is short, and no outcome or follow-up data are available. We therefore refrain from assigning clinical meaning to the observed transition density or entropy. The most defensible interpretation is that these quantities capture different observable properties of a labeled movement sequence.

The results also caution against using activity composition alone as a complete description of an observed movement sequence. Two participants can have the same ambulatory percentage but different median bout durations, longest inactive bouts, or transition rates. For gerontology measurement studies in which temporal patterning matters, a compact reporting set could include total ambulatory percentage, one continuity measure, and one organization measure, together with the state map and monitoring context. This reporting principle is portable across settings, whereas the numerical estimates from HAR70+ are not. The measures require validation in longer free-living recordings before any use in surveillance, clinical assessment, or risk stratification.

4.1 Strengths and limitations

Strengths include transparent public data, validated activity labels, two-sensor acquisition, coverage of adults up to 95 years of age, participant-level analysis, bootstrap uncertainty, and a fully reproducible transformation from samples to bouts. The use of explicit labels avoids equating low acceleration with sitting when posture information is available.

The limitations are substantial. Eighteen participants provide limited precision for correlation analysis. The protocol was semi-structured and lasted approximately 40 minutes, so estimates are not daily averages. Participants may not represent older adults with severe mobility limitations or diverse living environments. Activity labels and bout boundaries inherit any source-annotation error. Transition density gives each label change equal weight and does not distinguish planned task switching from unstable movement. Entropy summarizes distribution rather than sequence order. Finally, the analysis is cross-sectional and contains no clinical outcome, preventing causal or prognostic inference.

5 Conclusions

In HAR70+, activity amount, bout continuity, and state-transition organization conveyed different information about the labeled movement sequence. Ambulatory activity occupied about half of the semi-structured protocol, active bouts were short, and transition density varied across participants. These results support reporting temporal organization alongside activity composition in methodological studies, while underscoring that a short benchmark cannot substitute for free-living monitoring or clinical validation.

Declarations

Ethics approval and consent to participate

This study was a secondary analysis of an openly distributed, de-identified dataset and involved no new participant contact or intervention. Ethical oversight and consent for the original data collection are described by the dataset creators. The present analysis did not attempt re-identification.

Consent for publication

Not applicable. This manuscript does not contain identifiable individual participant data.

Availability of data and materials

HAR70+ is publicly available from the UCI Machine Learning Repository at DOI 10.24432/C5CW3D. The accompanying reproducibility package contains the analysis code, derived participant-level tables, results summary, and a README describing the package contents.

Competing interests

[To be completed after author confirmation.]

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[To be completed after author confirmation.]

Authors' contributions

W.Z.: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Writing – review and editing, and Project administration.

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Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- ZhaoHAR70ReproducibilityMaterials.zip