Original Paper

Average Acceleration as a Measure of Physical Activity Across Sensor Locations in Participants With Heart Failure or Chronic Obstructive Pulmonary Disease and Healthy Volunteers: Secondary Analysis

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Abstract

Background: Average acceleration derived from wearable sensors offers a simple, continuous measure of physical activity and mobility that may overcome the limitations of complex accelerometer algorithms or site-based assessments in clinical trials. However, evidence supporting the use of average acceleration in patients with heart failure (HF) and/or chronic obstructive pulmonary disease (COPD) remains limited.

Objective: This study aimed to evaluate how average acceleration can be used to assess walking-related outcomes in both laboratory and free-living settings and to assess the influence of sensor location on these measurements in participants with HF or COPD and healthy volunteers.

Methods: Using data from the Mobilise-D Technical Validation Study, including structured, laboratory-based tasks and free-living assessments using sensors placed on the foot, lower back, and wrist, we analyzed average acceleration metrics computed as Euclidean norm minus one (ENMO), ENMO >0, and Euclidean norm (EN) from band-pass filtered triaxial acceleration (0.29-10 Hz; fourth-order Butterworth). During walking bouts, average acceleration was correlated with walking speed and cadence for each sensor location and cohort (HF, COPD, and healthy adults); sensor-location effects and cohort-specific sensitivity were evaluated. Linear mixed-effects models included participants as random intercepts and walking speed as both a fixed effect and a random effect.

Results: Average acceleration showed a strong positive association with walking speed during straight-walking laboratory tasks across all sensor locations, with foot sensors showing the strongest association, followed by lower-back sensors and then wrist sensors. In complex walking tasks and free-living walking bouts, the strength of these associations decreased, and location effects were more pronounced. Across cohorts during free living, filtered EN r^2 ranged from 0.711 to 0.818 for the foot, from 0.439 to 0.673 for the lower back, and from 0.067 to 0.146 for the wrist. The strength of the association for wrist data improved only during free-living sustained walking bouts (>10 seconds), although these associations were weaker than those for the foot and lower back. The Pearson correlation was marginally stronger for ENMO >0 than for filtered EN, but filtered EN preserved more signal by mitigating the influence of gravity and noise. Linear mixed-effects models showed that the variance could be largely attributed to stable participant-specific differences.

Conclusions: Average acceleration showed potential as a measure for capturing walking-related activity in adults with HF or COPD and in healthy adults when using appropriate sensor placement. The strength of the association depended strongly on sensor placement, with the foot showing the most consistent relationship, the lower back providing a reasonable alternative,

and the wrist showing weaker performance, particularly during free living. We recommend that trials use standardized reporting of sensor location, filtering parameters, and walking-bout definitions and prioritize foot or lower-back placement for walking-related end points.

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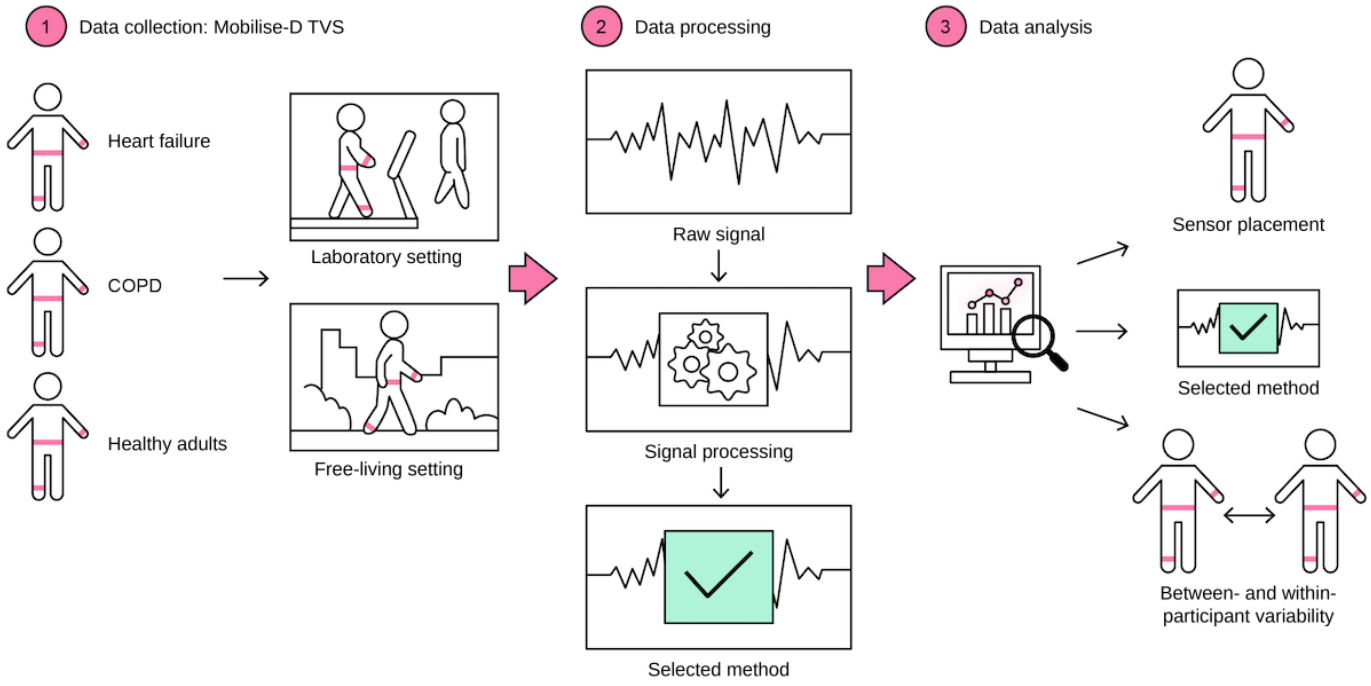
Keywords: average acceleration; heart failure; chronic obstructive pulmonary disease; exercise; wearable accelerometer; walking

Introduction

Patients with chronic diseases such as heart failure (HF) or chronic obstructive pulmonary disease (COPD) may experience physical function impairment, complicated by symptoms such as dyspnea and fatigue [1,2]. Qualitative research has shown that dyspnea and fatigue in patients with HF are associated with walking distance and walking speed, often resulting in patients either resting during bouts of activity, performing activities at a lower intensity, or avoiding physical activity altogether [3]. In a gait analysis of patients with COPD, walking speed and cadence were shown to be significantly lower with increasing disease severity [4]. Guidance from the US Food and Drug Administration emphasizes the importance of improving physical functioning as an end point in patients with HF, even in the absence of a favorable effect on survival or the risk of hospitalization [5]. Accurately measuring real-world mobility is essential for both clinical research and patient monitoring in populations with chronic health conditions [6]. Physical function is commonly assessed using patient-reported outcomes (widely used in clinical trials) and in-clinic assessments such as the 6-minute walk test (6MWT), which is regularly used to assess physical function in patients with HF or COPD [3,7]. However, these approaches have limitations, including assessments being conducted at limited time points, reliance on self-reporting (which may be subjective), the need for patients to visit an appropriately equipped test center, and the fact that some therapies demonstrate inconsistent changes or no change in 6MWT results compared with other outcomes [7-11]. These limitations prevent a full understanding of real-world activity patterns and their change over time.

Accelerometers can be used as a patient-centric alternative to assess physical function, enabling continuous or selected remote assessments [6,9,10,12]. Although deriving measures such as walking distance and walking speed with high precision using accelerometers is challenging [13], average acceleration has been identified as a simpler, direct measure of movement that is closely related to the raw accelerometer data and has a low estimation error [10]. However, evidence supporting the use of accelerometers and digital mobility outcomes such as average acceleration to characterize real-world mobility is limited, particularly among patients with chronic diseases [9]. In addition, accelerometers can be placed at various locations on the body; however, the information provided by acceleration is sensitive to the location at which they are worn [12]. For instance, devices worn on the wrist are generally preferred by patients and are associated with greater compliance, but they detect arm movements in addition to ambulation [10,12,14], whereas sensors worn on the lower back are technically robust and have historically been validated in research and clinical contexts [13]. Prior work in the laboratory setting indicates high correlations between wrist and hip during walking, but complex activities and free-living conditions show location-dependent differences [12]. Raw average acceleration data can be processed using various methods to reduce artifacts due to noise and gravitational and movement-related components of the acceleration signal [15]. Further research is needed to assess the validity and metrological performance of accelerometers in patients with HF or COPD and the influence of sensor location on the interpretability and comparability of measurements. The Mobilise-D Technical Validation Study (TVS), which aimed to validate a digital mobility assessment tool under real-world conditions, offers a comprehensive, multistage validation protocol, and a comprehensive reference system to validate findings [9]. Data included demographic and clinical characteristics of participants, raw and processed sensor data, and reference gait parameters from multiple disease cohorts and healthy individuals [9]. Data were collected using wearable sensors worn simultaneously at multiple locations, which captured a wide range of gait parameters and contextual information in both controlled and free-living settings [9]. This analysis used anonymized data from the Mobilise-D TVS [9] to evaluate the best metric for average acceleration, to assess how average acceleration could be used to capture walking-related concepts in both laboratory and free-living settings, and to analyze the impact of sensor location on these outcomes in patient populations with symptomatic diseases (HF and COPD) and healthy adult (HA) volunteers (Figure 1). The HF and COPD cohorts represent cardiovascular and respiratory populations with conditions that have a symptomatic impact on physical activity [1].

Figure 1. Study schema. COPD: chronic obstructive pulmonary disease; TVS: Technical Validation Study.



Methods

Population

This study was a secondary analysis of anonymized observational data from 3 cohorts included in the Mobilise-D TVS: participants with HF, those with COPD, and HA volunteers. The eligibility criteria for these cohorts have been previously described [9]. In short, participants with HF and COPD were aged ≥45 years and had a diagnosis of either chronic HF with a grading of II to IV on the New York Heart Association Classification or COPD with a postbronchodilator ratio of forced expiratory volume in 1 second (FEV_1) to forced vital capacity of <0.70, respectively. HA participants were aged ≥65 years, and all participants were able to walk 4 m independently (with or without a walking aid) [9]. In addition, participants with data from all 3 sensor locations (right foot, lower back, and left wrist) were included in this analysis.

Data Collection and Protocols

Data in the Mobilise-D TVS were collected through simultaneous recordings from a multisensory system (Inertial Module with Distance Sensors and Pressure Insoles [INDIP] [16]; McRoberts BV; 100 Hz sampling frequency), comprising sensors worn on the nondominant wrist, lower back, and feet, and from the DynaPort MM+ device (McRoberts BV; 100 Hz sampling frequency), worn on the lower back via an elastic waistband [9]. The INDIP system was used to define walking bouts and provide reference measurements for speed and cadence. Device calibration, placement, and synchronization have been previously described [9].

This study used deidentified data from the Mobilise-D TVS. The original study (International Standard Randomized Controlled Trial Number 12246987) [17] was approved by local ethics committees at each recruitment site and written informed consent was obtained from participants [9].

Data from both laboratory-based structured assessments and real-world validation assessments were included in the analysis. Laboratory-based assessments consisted of structured, task-based mobility activities, including straight walking (at 3 different speeds) and complex walking (including straight walking, the timed up and go test, the L-test, the surface test, and the hallway test) [9]. Real-world validation consisted of an unsupervised 2.5-hour observation period in a habitual environment (free-living assessment). The INDIP system and DynaPort MM+ sensors were worn for both laboratory and real-world assessments.

The main outcomes assessed were the strength of the relationship between average acceleration and both walking speed and cadence during walking bouts, stratified by sensor location and cohort; the effect of sensor location on average acceleration measurements; and the differences in the acceleration–walking speed relationship across sensor locations, using mixed-effects comparisons that controlled for participant random effects.

Data Processing

Raw data were derived using 3-axis acceleration at 100 Hz during INDIP-defined walking bouts. The Mobilise-D pipeline algorithm has been previously reported [13]. Raw accelerometry signals were processed using 3 metrics: Euclidean norm minus one (ENMO); ENMO >0 (in which negative values were set to 0); and band-pass filtered Euclidean norm (EN) using a fourth-order Butterworth filter (0.29-10 Hz) [18] to mitigate the influence of gravity (low-frequency components) and noise (high-frequency components), thereby producing EN (or vector magnitude units) from filtered data. Aggregation windows included bout-level metrics and summaries over the

full laboratory-based structured tests (straight walking and complex walking) and free-living walking bouts.

Metric Selection

ENMO, ENMO >0, and band-pass filtered EN metrics were compared to select the most appropriate measure of average acceleration. Metrics were evaluated based on their ability to remove nonmovement signal components (gravity and noise) while preserving movement-related signals. Pearson correlations between walking speed and average acceleration calculated using each metric were assessed during straight-walking laboratory tests. R^2 values were computed across all sensors, participants, and cohorts to quantify the strength of the linear relationship with walking speed for each metric.

Statistical Analysis

Descriptive statistics, including mean (SD), median (IQR), and distribution analyses, were used to describe patient demographics and characteristics. Pearson r and linear regression were used to assess the relationships between acceleration and both walking speed and cadence. Correlations were assessed using all available walking bouts for the laboratory-based structured tasks and free-living mobility assessments, and separately for each participant during free-living mobility assessments. For the participant-specific analyses, 1 Pearson correlation coefficient was calculated for each participant, sensor location, and processing metric using that participant's available walking bouts. Because multiple walking bouts were contributed by each participant, pooled correlation estimates were interpreted descriptively and did not account fully for within-participant dependence. For the laboratory-based structured tasks, linear mixed-effects models (LMMs) were used to account for the hierarchical structure of the data, in which repeated gait measurements were nested within participants. It is expected that, owing to shared underlying characteristics, gait parameters from the same individual will be correlated even when performing different tests or walking at different speeds. LMMs accommodate this within-patient dependence through patient-specific random effects, differentiating between-participant and within-participant variability. Two models were compared: a baseline model with random intercepts for the participants, and an enhanced model that added random slopes for walking speed. The latter model allows both baseline gait levels and gait–walking speed relationships to vary by participant. The mixed-effects models were evaluated using the Akaike information criterion (AIC), Bayesian information criterion (BIC), and intraclass correlation coefficient (ICC). The sensitivity analyses performed were comparisons of filtered EN and ENMO >0 metrics, laboratory-based structured straight walks and complex tasks, and free-living walking-bout durations (<10 seconds vs ≥10 seconds). Analyses were performed using Python (version 3.9.7; Python Software Foundation) with the following packages: *scipy.signal* for signal processing, *scipy.stats* for correlations, and *statsmodels* for mixed models.

Ethical Considerations

This secondary analysis used deidentified data in accordance with the original study's ethical approvals. The Mobilise-D TVS was approved by institutional review boards or ethics committees at participating sites (International Standard Randomized Controlled Trial Number 12246987).

Results

Participant Demographics and Characteristics

Overall, data were included from 11, 16, and 20 participants in the HF, COPD, and HA cohorts in the Mobilise-D TVS dataset, respectively. Participant demographics and clinical characteristics for the different cohorts are shown in Table 1. The HF cohort had a mean 6MWT distance of 370.6 (SD 115.6) m and a mean Kansas City Cardiomyopathy Questionnaire–12 (KCCQ-12) score of 80.7 (SD 20.3). This indicates moderately reduced exercise capacity, with predominantly mild to moderate symptoms and limitation. The COPD cohort had a mean 6MWT distance of 354.4 (SD 90.4) m, a mean FEV_1 of 1.6 (SD 0.6) L, and a mean COPD assessment test (CAT) score of 19.7 (SD 9.2), indicating a high symptom burden but preserved ambulation. Lower-limb function (Late-Life Function and Disability Instrument [LLFDI]) was lowest in the COPD cohort.

Table 1. Participant demographics and characteristics stratified by cohort.

Characteristics	Participants with heart failure (n=11)	Participants with COPD[a] (n=16)	Healthy adults (n=20)
Age (years), mean (SD; range)	67.7 (11.3; 47-85)	69.8 (9.2; 53-81)	71.7 (5.8; 65-89)
Female, n (%)	4 (36.4)	7 (43.8)	9 (45)
Height (cm), mean (SD)	174.5 (10.4)	169.3 (6.7)	166.4 (10.2)
Weight (kg), mean (SD)	85.3 (17.3)	73.8 (14.7)	75.1 (11.8)
BMI (kg/m^2), mean (SD)	28.0 (4.9)	25.9 (5.4)	27.1 (3.6)
6-minute walk test distance (m), mean (SD)	370.6 (115.6)	354.4 (90.4)	—[b]
Late-Life Functional and Disability Instrument, mean (SD)	67.5 (22.4)	59.2 (8.2)	73.5 (14.2)
Kansas City Cardiomyopathy Questionnaire–12 (0-100), mean (SD)	80.7 (20.3)	—	—
COPD assessment test (0-40), mean (SD)	—	19.7 (9.2)	—
Forced expiratory volume in 1 second (L), mean (SD)	—	1.6 (0.6)	—

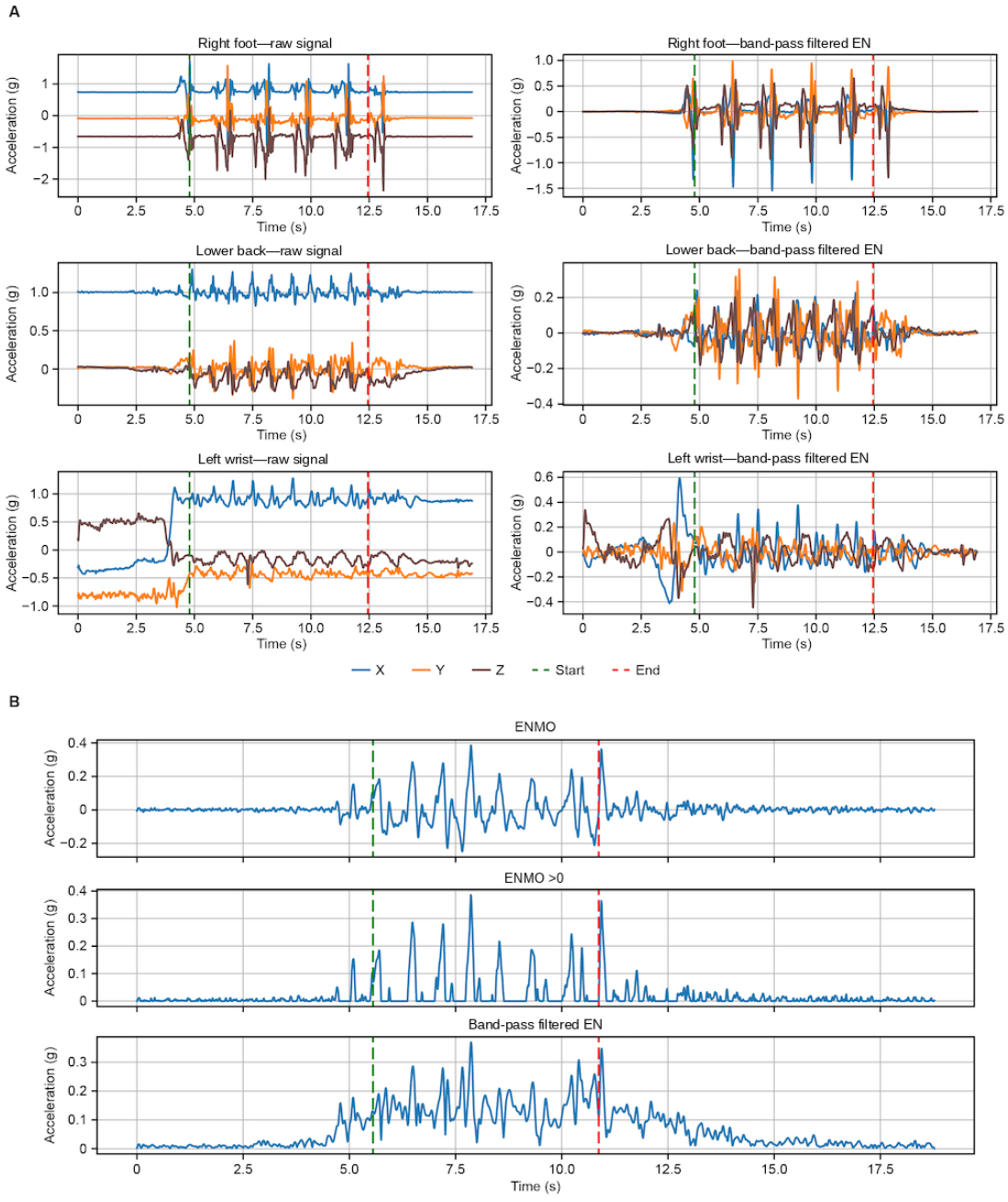
[a]COPD: chronic obstructive pulmonary disease.
[b]Data not available.

Metric Comparison

Comparative analysis showed that band-pass filtered EN preserved the majority of the signal while mitigating the impact of nonmovement components, such as gravity, with the filtered signal for all axes centered around 0 (Figure 2A and B). Comparison of R^2 values indicated differences in the strength of the linear relationship with walking speed: ENMO >0 (R^2=0.92), filtered EN (R^2=0.85), and raw ENMO (R^2=0.79). Although ENMO >0 showed the strongest Pearson correlation with walking speed, it discards genuine low-magnitude activity because it constrains negative values to zero. Raw ENMO produced nonphysical negative values and, subsequently, was not used in further calculations.

Filtered EN consistently demonstrated higher median acceleration and a lower coefficient of dispersion than ENMO >0, indicating better signal stability. By balancing signal quality with artifact removal and preservation of signal continuity, filtered EN was selected as the primary metric for all subsequent analyses.

Figure 2. (A) Raw and band-pass filtered accelerometer data from all sensor locations and (B) comparison of Euclidean norm minus one (ENMO), ENMO >0, and band-pass filtered Euclidean norm (EN) metrics from wrist sensor from 1 participant.



Average Acceleration

Summaries of the relationships between ENMO >0 and filtered EN acceleration and walking speed and cadence for both laboratory and free-living data are presented in Table 2 and Table S1 in Multimedia Appendix 1. When combining assessments from all patients in a cohort, for laboratory-based, straight-walking assessments, there was a strong positive linear association between average acceleration and walking speed across all sensor locations, with the strongest correlations generally for the foot sensor location, followed by the lower back and wrist (Figure 3A). Average acceleration showed a strong positive linear association with cadence for all sensor locations (Figure 3B). As observed with walking speed, the strongest associations were observed for the foot sensor, followed by the lower back and then the wrist. During more complex laboratory-based walking tasks (eg, those involving turns), the associations were not as strong as those for straight walking alone; however, the pattern of stronger associations for the foot and lower-back sensors persisted (Figure 4 and Figure S1A in Multimedia Appendix 1). During free-living assessments, the associations between average acceleration and walking speed generally remained strong for the foot and lower-back sensors; however, the association for the wrist sensor was weaker than that observed during the laboratory assessments (Figure 5 and Figure S1B in Multimedia Appendix 1). Additionally, analysis of participant-specific Pearson correlations between average acceleration and walking speed across all cohorts showed that the median Pearson r and R^2 were highest for the foot sensors, which also had the lowest IQR, followed by the lower back and then the wrist (Figure 5). Generally, the observed correlations were greater for walking speed than for cadence. Approximately half of the recorded walking bouts exceeded 10 seconds, and longer bouts (>10 seconds) generally exhibited higher walking speeds than shorter bouts (≤10 seconds). For the wrist sensor, the strength of the linear association improved more for longer walking bouts; no corresponding pattern was observed in the foot and lower back sensors (Table 3). Although too few participants (n=3) used walking aids during the free-living observation period to draw any definitive conclusions, using a cane did not seem to impact foot and lower-back associations, whereas negative correlations were sometimes observed for the wrist sensors (Figure 6). Similar trends were observed among participants using rollators, who walked more slowly than the rest of the study population.

Figure 3. Correlation between average acceleration and (A) walking speed and (B) cadence during straight walking across all cohorts. COPD: chronic obstructive pulmonary disease; EN: Euclidean norm; HF: heart failure.

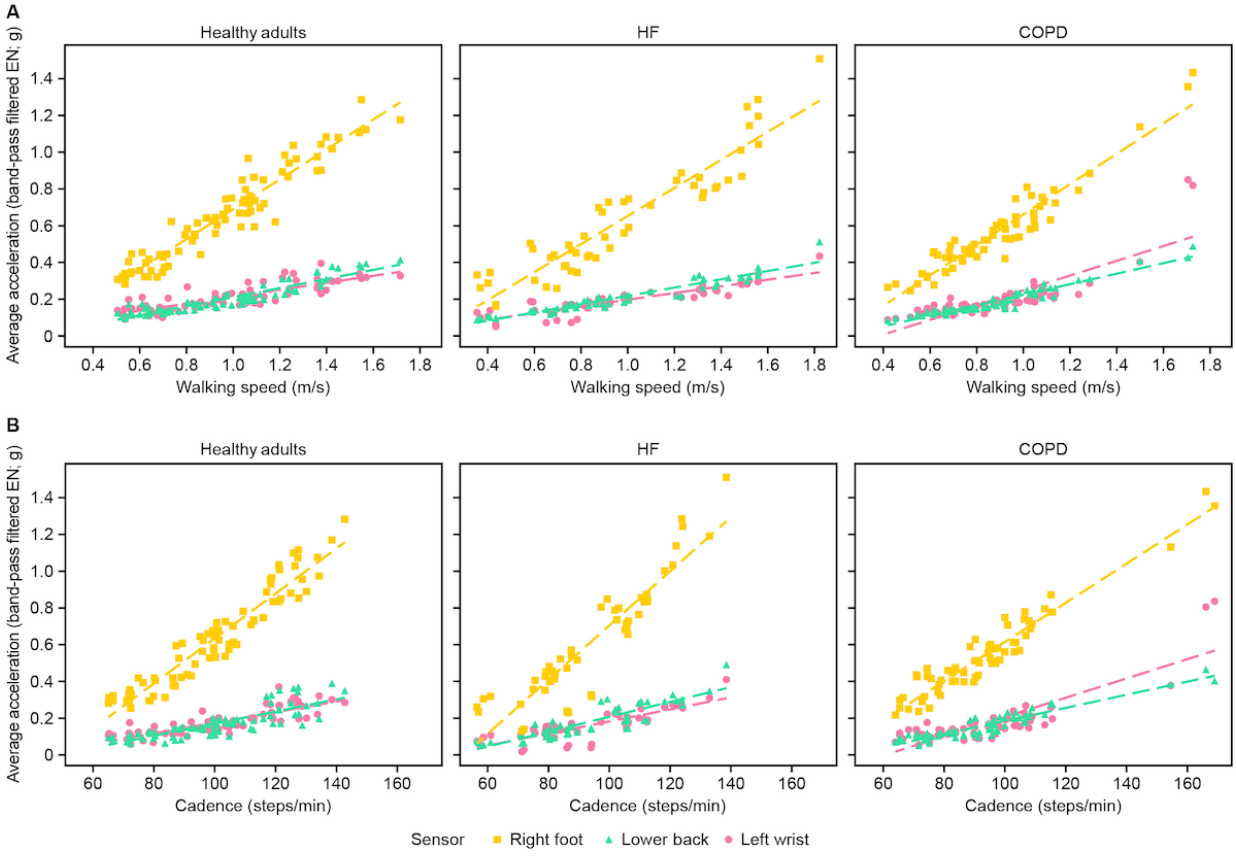


Figure 4. Correlation between average acceleration and walking speed during complex walking across all cohorts. Complex walking comprises straight walking, the timed up and go test, L-test, surface test, and hallway test. COPD: chronic obstructive pulmonary disease; EN: Euclidean norm; HF: heart failure.

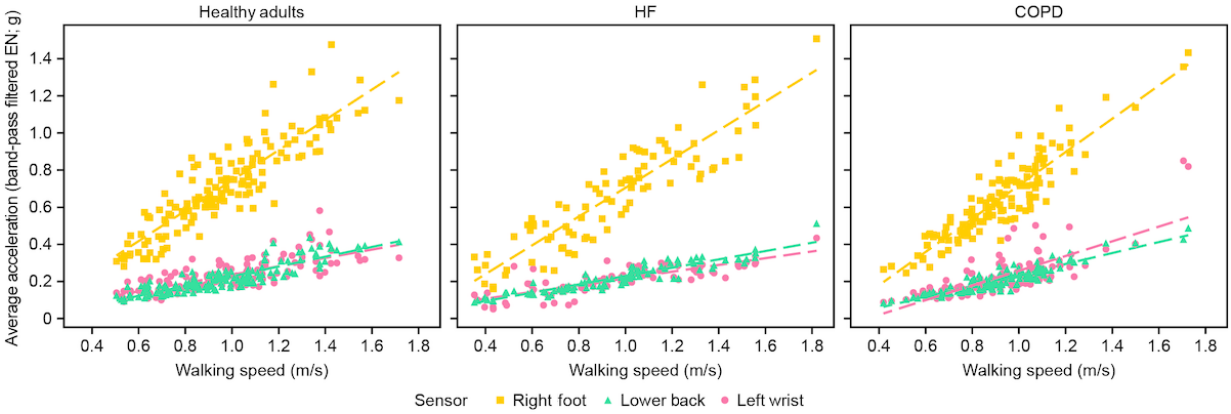


Figure 5. Correlation between average acceleration and walking speed during free-living walking bouts: (A) scatterplots showing the correlations across all cohorts and (B) boxplots comparing the distribution of participant readings, stratified by sensor location. COPD: chronic obstructive pulmonary disease; ENMO: Euclidean norm minus one; HA: healthy adult; HF: heart failure.

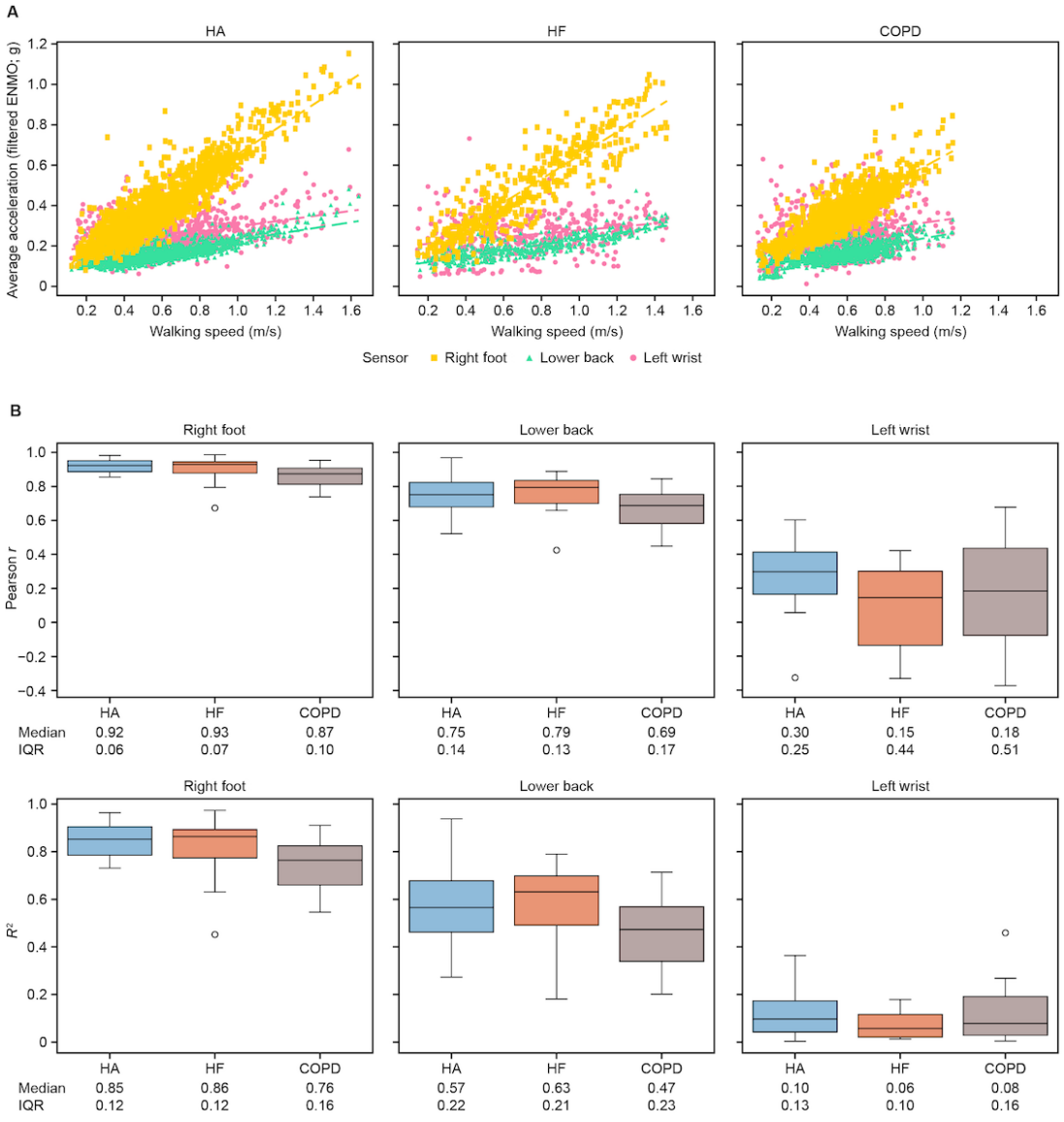


Figure 6. Correlation coefficients between average acceleration and walking speed during free-living walking bouts for patients using walking aids.

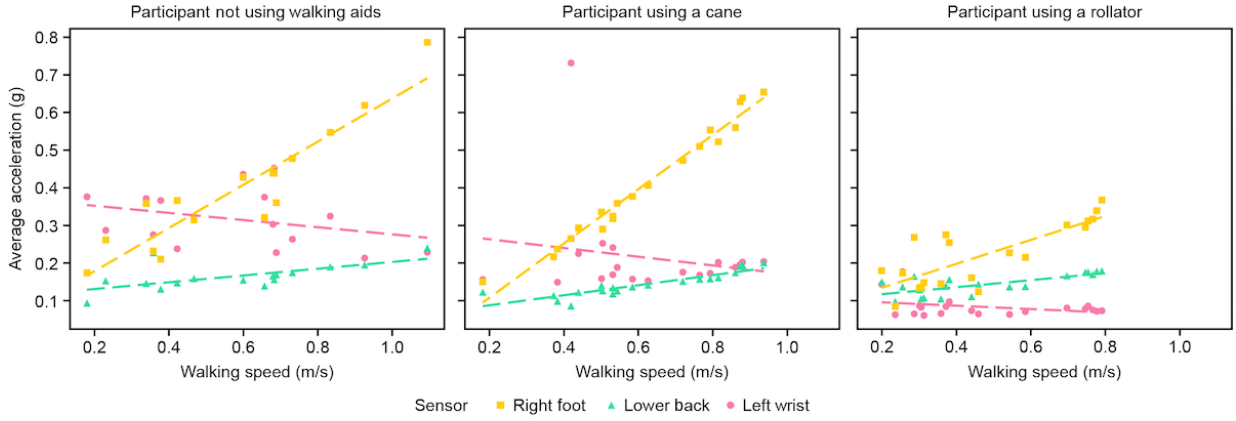


Table 2. Linear correlation between acceleration and walking speed, stratified by sensor location, cohort, and laboratory-based straight walking, all laboratory-based tests or free-living.

Sensor locations	ENMO[a]>0						Filtered EN[b]					
	Straight walking		All laboratory tests		Free-living		Straight walking		All laboratory tests		Free-living	
	r	R^2	*r*	R^2	*r*	R^2	*r*	R^2	*r*	R^2	*r*	R^2
Right foot												
HA[c]	0.954	0.909	0.901	0.811	0.924	0.854	0.954	0.910	0.887	0.787	0.904	0.818
Patients with HF[d]	0.932	0.868	0.916	0.839	0.921	0.848	0.934	0.872	0.907	0.823	0.903	0.815
Patients with COPD[e]	0.953	0.909	0.922	0.851	0.876	0.767	0.951	0.904	0.909	0.825	0.843	0.711
Lower back												
HA	0.948	0.898	0.892	0.795	0.852	0.727	0.928	0.860	0.874	0.763	0.758	0.575
Patients with HF	0.926	0.858	0.914	0.835	0.877	0.768	0.955	0.912	0.933	0.870	0.820	0.673
Patients with COPD	0.955	0.912	0.916	0.840	0.760	0.578	0.959	0.920	0.918	0.843	0.663	0.439
Left wrist												
HA	0.791	0.625	0.759	0.577	0.617	0.381	0.835	0.697	0.736	0.542	0.382	0.146
Patients with HF	0.873	0.761	0.804	0.647	0.595	0.354	0.899	0.807	0.809	0.654	0.283	0.080
Patients with COPD	0.742	0.551	0.705	0.497	0.433	0.187	0.821	0.674	0.762	0.581	0.258	0.067

[a]ENMO: Euclidean norm minus one.
[b]EN: Euclidean norm.
[c]HA: healthy adult.
[d]HF: heart failure.
[e]COPD: chronic obstructive pulmonary disease.

Table 3. Correlation coefficients between average acceleration and walking speed, stratified by walking-bout duration.

Sensor locations	ENMO[a]>0				Filtered EN[b]			
	≤10 seconds		>10 seconds		≤10 seconds		>10 seconds	
	r	R^2	*r*	R^2	*r*	R^2	*r*	R^2
Right foot								
HA[c]	0.907	0.823	0.933	0.871	0.889	0.791	0.908	0.825
Patients with HF[d]	0.922	0.851	0.922	0.850	0.916	0.839	0.897	0.804
Patients with COPD[e]	0.869	0.755	0.885	0.784	0.858	0.737	0.828	0.685
Lower back								
HA	0.848	0.719	0.858	0.736	0.677	0.458	0.800	0.639
Patients with HF	0.850	0.723	0.897	0.804	0.780	0.609	0.858	0.736
Patients with COPD	0.804	0.646	0.729	0.532	0.655	0.429	0.672	0.452
Left wrist								
HA	0.505	0.255	0.664	0.441	0.280	0.078	0.462	0.214
Patients with HF	0.461	0.212	0.685	0.469	0.192	0.037	0.453	0.205
Patients with COPD	0.389	0.152	0.474	0.225	0.204	0.042	0.319	0.102

[a]ENMO: Euclidean norm minus one.
[b]EN: Euclidean norm.
[c]HA: healthy adult.
[d]HF: heart failure.
[e]COPD: chronic obstructive pulmonary disease.

Between- and Within-Participant Variability

A comparison of model fit for LMMs using AIC, BIC, and ICC is presented in Table 4. When incorporating walking speed as random slope, the models consistently performed better across all metrics, indicating that there are differences between participants in their baseline gait characteristics and in how gait parameters varied with walking speed in the same participant. The random-slope models showed lower AIC and BIC and higher ICC across all sensors and processing approaches, indicating between-participant differences in baseline acceleration and in the relationship between walking speed and acceleration.

Table 4. Linear mixed-effects model fit comparison: random intercept only (baseline) vs random intercept+random slope (RS)[a] models for Euclidean norm minus one (ENMO) >0 and filtered Euclidean norm (EN) by sensor location.

Cases	AIC[b]			BIC[c]			ICC[d]		
	Baseline	Baseline+RS model	ΔAIC[e]	Baseline	Baseline+RS model	ΔBIC[f]	Baseline	Baseline+RS model	ΔICC[g]
ENMO >0									
Right foot	–754.6	–785.8	31.2	–731.3	–754.7	23.4	0.325	0.94	0.615
Lower back	–1991.1	–2044.7	53.6	–1967.8	–2013.6	45.8	0.239	0.89	0.651
Left wrist	–1154.7	–1364.3	209.6	–1131.3	–1333.2	201.9	0.208	0.987	0.779
Filtered EN									
Right foot	–664.2	–672.8	8.6	–640.8	–641.7	0.9	0.316	0.896	0.58
Lower back	–1495	–1529.8	34.8	–1471.6	–1498.6	27	0.3	0.896	0.596
Left wrist	–995.1	–1096.4	101.3	–971.7	–1065.3	93.6	0.186	0.974	0.788

[a]RS was the model preference for all sensor locations.
[b]AIC: Akaike information criterion.
[c]BIC: Bayesian information criterion.
[d]ICC: intraclass correlation coefficient.
[e]ΔAIC: difference between AIC at baseline and baseline+RS model.
[f]ΔBIC: difference between BIC at baseline and baseline+RS model.
[gi]ΔICC: difference between ICC at baseline and baseline+RS model.

Discussion

Principal Findings

This study explored the association between average acceleration and activity levels across physical activity experiments, sensor placements, and different methods of raw acceleration data processing. Using walking speed and cadence as reference measures, this analysis evaluated average acceleration as a potential surrogate measure for these gait metrics. This study demonstrated that average acceleration is potentially a practical, interpretable measure of walking-related physical activity. There were strong positive linear associations between average acceleration and both walking speed and cadence across all sensor locations during laboratory-based straight-walking assessments. These associations remained evident during more complex laboratory-based walking tasks, although the associations were weaker than those observed during straight walking. Furthermore, the utility of acceleration data depends on sensor location; foot placement consistently provided the strongest associations with walking speed and cadence, while placement on the lower back also provided a robust alternative. The wrist sensor was found to have the weakest associations with walking speed and cadence during laboratory-based assessments, with even more so during the free-living assessment, in which arm movements during daily activities may have confounded the signals (as acceleration is a direct measure of movement at the sensor location). However, the strength of the linear associations between average acceleration and walking speed for wrist placement increased with longer walking bouts.

The choice of data processing metric can also enhance interpretability and reduce artifacts. By setting negative values to 0, ENMO >0 may miss potentially meaningful low-intensity movement signals, and in some cases, ENMO values can be truly negative. In contrast, a large portion of the ENMO signals consist of negative values (eg, due to noise or artifacts), resulting in smaller average values than those obtained using ENMO >0 and band-pass filtered EN. In addition, when using ENMO, the values of the accelerometer axis parallel to gravity are disproportionately weighted compared with those from the other 2 axes; thus, a change in acceleration in the axis with the largest gravitational component will have a much greater influence of the total ENMO value than changes along the other axes, which

are generally closer to 0. Band-pass filtered EN appears to improve signal quality, whereas the ENMO >0 method resulted in a marginally stronger correlation between average acceleration and walking speed but may sacrifice low-intensity movement data. The choice of metric therefore depends on the study objective.

Adding walking speed as a random slope improved model fit (lower AIC and BIC) and increased the ICC across all sensor locations and processing approaches. This indicates that participants differed both in their baseline average acceleration and in how acceleration scaled with walking speed. The higher ICC should be interpreted cautiously: part of the increase reflects the random slope absorbing within-participant variance, and the ICC in random-slope models depends on the speed at which it is evaluated. Our design cannot establish whether these participant-level differences reflect physiological factors (eg, body size and gait strategy), disease-related adaptations (eg, dyspnea or fatigue altering how speed is increased), or methodological factors (eg, sensor attachment and orientation). Disease group, severity, and anthropometric covariates were not modeled and should be tested in future work.

Regardless of the source, these findings have practical implications. For longitudinal monitoring and digital mobility end points, changes in average acceleration are best interpreted relative to each individual's own baseline and speed-acceleration relationship rather than to group norms alone. For study design, trials should collect repeated measures across a range of walking speeds and use mixed-effects models with random intercepts and slopes, accounting for between-participant variability in sample size planning. The greater variability observed at the wrist further supports foot or lower-back placement when walking is the target outcome.

These findings have implications for trials involving patients with HF or COPD that target walking outcomes; average acceleration may serve as a digital end point that is complementary to more complex gait measures. These results align with previous findings validating algorithms from lower-back sensors [13]. In addition, these data consistently suggested that sensors placed on the foot or lower back reflect walking characteristics better than those placed on the wrist placement. For future studies that include average acceleration as an outcome, we recommend consistent reporting of sensor location, filtering parameters, and walking-bout definitions.

Strengths and Limitations

The strengths of this study include the well-characterized dataset from the Mobilise-D TVS, comprising laboratory-based, structured tasks and assessments as well as multilocation sensors, which allowed for a thorough analysis of sensor locations across a variety of activities. Participants with cardiovascular and respiratory diseases affecting walking ability (HF and COPD) were included, in addition to a healthy control cohort. Data from the INDIP system sensors provided reference measurements for walking bouts and for segments of walking speed and cadence. We also acknowledge the limitations of this analysis: generalizability to activities other than walking was not assessed. In addition, HF and COPD were the only diseases evaluated beyond the healthy volunteer cohort.

Further research is warranted to validate these findings. Average acceleration should be evaluated during free-living periods using established end points and measures of disease severity. In addition, standardized sensor placement on the foot and/or lower back should be evaluated for walking end points with predefined equivalence margins (for example, $r \geq 0.7$ and a slope within ±10%) and evaluated across participants with varying disease severity. Wrist-based associations using bout-duration thresholds should be further validated with prespecified cutoffs and handling of missing values during free-living assessments. Finally, there is a need to establish a preprocessing standard (eg, Butterworth filtering at 0.29-10 Hz, vector magnitude, and ENMO >0 vs band-pass filtered EN) and to report sensitivity to filter parameters across sensor locations.

This study was limited by the relatively small sample size, the repeated and potentially nonindependent observations contributed by each participant, and the absence of formal agreement, equivalence, or replacement analyses to determine whether average acceleration can be used interchangeably with walking speed or cadence. The selected 0.29 Hz lower cutoff of the band-pass filter may attenuate very-low-frequency components of movement, which could be particularly relevant during slow walking, although the filtered EN measure was intended to quantify movement magnitude rather than detect individual steps or estimate walking cadence.

Conclusions

Average acceleration is a straightforward and feasible measure for assessing walking-related physical activity levels among participants with HF, COPD, and HAs. When assessing walking-related activities in this study, foot placement showed the strongest associations, and lower-back placement showed a reasonable alternative pattern of association; wrist sensors should be used with caution, particularly in free-living settings, because they showed greater variability and weaker observed associations with walking speed and cadence. Band-pass filtering of data is recommended to preserve most of the sensor signal while reducing artifacts, whereas ENMO >0 may provide a slightly better correlation with walking speed. Future research should report sensor location, filtering parameters, and bout definitions to enhance comparability and interpretation.

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Generative AI Use

The authors declare that generative AI tools, including ChatGPT (AstraZeneca; OpenAI), were used during manuscript preparation for language refinement, grammatical correction, editing, and formatting to improve clarity and readability. These tools were not used to generate or interpret the study data, draw scientific conclusions, or develop the manuscript's substantive content. The authors reviewed and approved all AI-assisted text and remain fully responsible for the accuracy, integrity, and originality of the manuscript.

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Data Availability

Data from the Mobilise-D Technical Validation Study are publicly available through Zenodo. Scripts to assist with reproducibility can be shared upon request.

Authors' Contributions

Conceptualization: LS, MT-E, H Shaw, RBL, H Sillén
Data curation: LS, MT-E, H Shaw
Formal analysis: LS, MT-E, H Shaw
Funding acquisition: H Sillén
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Methodology: LS, MT-E, H Shaw, RBL, H Sillén
Project administration: H Sillén
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Validation: LS, MT-E, H Shaw, RBL, H Sillén
Visualization: LS, MT-E, H Shaw, RBL, H Sillén
Writing – original draft: LS, MT-E, H Shaw, RBL, H Sillén
Writing – review & editing: LS, MT-E, H Shaw, RBL, H Sillén

Conflicts of Interest

LS was an Evinova employee when the research was conducted and is currently affiliated with Chalmers University of Technology, Gothenburg, Sweden. MT-E, H Shaw, RBL, and H Sillén are AstraZeneca (Evinova) employees and may hold stock in AstraZeneca.

Multimedia Appendix 1

Correlations between average acceleration and walking cadence across sensor locations, cohorts, and study settings.
[DOCX File (Microsoft Word File), 281 KB-Multimedia Appendix 1]

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Abbreviations

6MWT: 6-minute walk test
AIC: Akaike information criterion
BIC: Bayesian information criteria
CAT: COPD assessment test
COPD: chronic obstructive pulmonary disease
EN: Euclidean norm
ENMO: Euclidean norm minus one
FEV_1: forced expiratory volume in 1 second
HA: healthy adult
HF: heart failure
ICC: intraclass correlation coefficient
INDIP: Inertial Module with Distance Sensors and Pressure Insoles
KCCQ-12: Kansas City Cardiomyopathy Questionnaire–12
LLFDI: Late-Life Function and Disability Instrument
LMM: linear mixed-effects model
TVS: Technical Validation Study

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