Mobility of Older Adults: Gait Quality Measures are associated with Life-Space Assessment Score

Anisha Suri, MS[1]; Andrea L. Rosso, PhD[2]; Jessie VanSwearingen, PhD[3]; Leslie M. Coffman, DPT[3]; Mark S. Redfern, PhD[4]; Jennifer S. Brach, PhD[3]; Ervin Sejdić, PhD[1,4,*]

[1]Department of Electrical and Computer Engineering, Swanson School of Engineering, University of Pittsburgh, Pittsburgh

[2]Department of Epidemiology, School of Public Health, University of Pittsburgh, Pittsburgh

[3]Department of Physical Therapy, School of Rehabilitation Sciences, University of Pittsburgh, Pittsburgh

[4]Department of Bioengineering, Swanson School of Engineering, University of Pittsburgh, Pittsburgh

[*]Corresponding author

Ervin Sejdić (E.S.)
Associate Professor
Department of Electrical and Computer Engineering
Swanson School of Engineering
University of Pittsburgh
Pittsburgh, PA 15261, USA
E-mail: esejdic@pitt.edu
Phone: 412-624-0508
Web: www.imedlab.org

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Abstract

Background: **The relation of gait quality to real-life mobility among older adults is poorly understood. This study examined the association between gait quality, consisting of step variability, smoothness, regularity, symmetry and gait speed with the Life-Space Assessment (LSA).**

Methods: In community-dwelling older adults (N=232, age 77.5±6.6, 65% females), gait quality was derived from: a) an instrumented walkway: gait speed, variability and walk-ratio; and b) accelerometer: signal variability, smoothness, regularity, symmetry, and time-frequency spatiotemporal variables during 6-minute walk. In addition to collecting LSA scores, **cognitive functioning, walking-confidence, and falls were recorded. Spearman correlations (speed as covariate) and Random Forest Regression were used to assess associations between gait quality and LSA, and Gaussian-mixture modeling (GMM) was used to cluster participants.**

Results: Spearman correlations of ρ_p=0.11 (signal amplitude variability ML), ρ_p=0.15, ρ_p=-0.13 (symmetry AP-V, ML-AP), ρ_p=0.16 (power V) and ρ=0.26 (speed), all p<0.05 and marginally related, ρ_p=-0.12 (regularity V), ρ_p=0.11 (smoothness AP) and ρ_p=-0.11 (step-time variability), p<0.1 were obtained. The **cross-validated Random Forest model indicated good fit LSA prediction error of 17.77; gait and cognition were greater contributors than age and gender. GMM indicated two clusters**. Group-1(N=189) had better gait quality than Group-2(N=43): greater smoothness AP (2.94±0.75 vs 2.30±0.71); greater similarity AP-V (0.58±0.13 vs 0.40±0.19); lower regularity V (0.83±0.08 vs 0.87±0.10); greater power V (1.86±0.18 vs 0.97±1.84); greater speed (1.09±0.16 vs 1.00±0.16 m/s); lower step time CoV (3.70±1.09 vs 5.09±2.37) and better LSA (76±18 vs 67±18), $p_{adjusted}$**<0.004**.

Conclusions: **Gait quality measures taken in the clinic are associated with real-life mobility in the community.**

Keywords**:** Gait accelerometry, walkway gait analysis system, Community mobility, Random forest regressor, Gaussian mixture model

Introduction

Community mobility is an individual's movement outside of his home and is known to decline with age (1,2). In the United States alone, 31.7% of adults aged 65 years and older report difficulty in performing daily tasks such as walking 3 city blocks in a neighborhood (1). Some of the public health burdens associated with limited and restricted mobility in the older population include compromised health and limited cognitive function (2), injuries from falls (1,3), and decreased social interactions and overall a less frequent participation in civic life (2). This social burden of impaired mobility is increasing rapidly. By 2040, the United States is expected to have more than 81 million adults older than 65 years, and 15.4 million older adults will be expected to be unable to walk 2 to 3 blocks, potentially adding an estimated $42 billion to annual health care costs (4). Mobility disability is common but it is not an inevitable consequence of aging (5). Though environment is an important determinant of mobility (6), it is an individual's walking, thinking and individual perceptions that enable a person to successfully navigate in the community (7,8).

Walking, a common form of physical activity in daily life of older adults (9) is a highly skilled task that requires coordination, maintenance of an up- right posture and modulation during phases of gait cycle (10). This complex process allows one to be adaptable in real-life situations. These situations include, for example, variations in walking surface, elevation in land, need for dual-tasking and presence of a staircase (11). This ability to adapt is known to decline with age (12). Another perspective is to measure the achieved mobility of older adults in real-life as the spatial area that they navigate and their need for assistance in doing so; Life Space Assessment score (LSA) is a popular self-reported questionnaire, used to quantify mobility in a community (6,13). The LSA has been used to recognize that mobility can be affected by cognitive and functional factors (14,15) and to reveal what the patient actually does in real-life (6,13).

Although speed of walking is a typically measured gait characteristic and has proven to be a primary health indicator (16), it doesn't capture the integration of stepping with postural adjustments. Clinicians are interested in 'how' a person walks as one indicator of motor skill (10). **Gait quality is one method of evaluating how well a person walks. Quantitative measures of gait quality include pace, rhythm, stepping variability, asymmetry, and regularity** (17). **Accelerometry is an efficient method to objectively capture these measures** (18). Accelerations taken from sensor placement on the lower back are often used (19,20) to derive a number of metrics, such as smoothness, regularity, symmetry and variability, which are the descriptors of gait quality. **These are chosen because they capture motor skill during straight path walking, commonly experienced during steady state walking in the community(21). We collected gait in the laboratory and quantify smoothness as the harmonic ratio for measuring acceleration-deceleration pattern of the trunk** (20)**; regularity as entropy-rate for assessing the step-to-step predictability of acceleration signals** (22)**; symmetry (sometimes referred to as similarity) as cross-correlation between axes capturing the multi-dimensional aspect of walking and thereby quantifying agreement in contralateral motion while walking, or more precisely a measure to determine whether signals change phase at similar times** (23,24)**; and variability as step-time coefficient of variation accounting for stride to stride spatio-temporal fluctuations.**

The main hypothesis is that better gait quality is associated with better LSA. We assess this hypothesis by the following three aims. First, we examine associations between **laboratory-measured gait quality** and community mobility. We hypothesized that people with better gait quality consisting of less variability, greater smoothness, more regularity, more symmetry and a faster speed of walking will have better community mobility (higher LSA). **Second, we** show the importance of these gait quality measures in combination with other factors known to be important determinants **(or contributors)** of LSA; namely demographics (13,25), cognition (15), gait efficacy, and fall history (26). **Third,** we perform a cluster analysis to **group participants** based on gait quality. We hypothesize that the participants will form groups based upon gait quality measures that will be related to the LSA.

Methods

Study design and Population

This is a cross-sectional relational study of gait quality and community mobility. We utilize baseline data from a randomized control clinical trial, called the program for improving mobility in aging (PRIMA). **The participants come from the greater Pittsburgh metropolitan region and had to be able to get themselves to the clinic site for two intervention visits per week and so by default had access to reliable transportation.** Briefly, PRIMA is a single-blinded two-arm intervention trial intended to compare the effects of interventions on mobility, activity, and participation in older adults. Detailed methods of PRIMA have been fully introduced elsewhere (27). In this study, participants were at least 65 years of age, were able to walk household distances independently, had usual gait speed between 0.60 m/s and 1.20 m/s, and were able to follow two step commands.

Quantifying out-of-home mobility

Life Space Assessment (LSA) is a self-reported metric of a person's achieved mobility (13). The life-space levels range from an individual's bedroom (Level 1) to beyond the individual's town (Level 5). The assessment includes a series of three questions for each defined level as it pertains to the previous four weeks. For each level, the subject is asked whether he has been to that level, how often he has been to that level, and whether assistance was needed for mobility in that zone. Thus, for each of the five levels a score is obtained and finally these scores are summed to get a total LSA score. The composite LSA score ranges from 0 (totally bed-bound) to 120 (travelled out of town every day without assistance). Higher scores are indicative of greater community mobility.

Acceleration measures of walking

Gait data were collected during a six-minute walking test in a laboratory setting on an oval track which had a lap distance of 37.56 m (28)**.** The subject was asked to cover as much distance as possible during the allotted amount of time. **Before the test, five tri-axial accelerometers (Actigraph LLC; Pensacola, FL) were placed on the subject, one on each wrist and ankle and one on lower back (L3 level). The data used in this analysis was obtained from an accelerometer placed at the L3 spinal level as it is close to the center of mass of the body and accelerations measured by a single sensor at this location can better represent the major human motion** (19) (**eFigure 1A** in the Supplement). Accelerometer data were sampled at 100 Hz in most cases. **Accelerations from 29 (12.5%) subjects were sampled at 30 Hz due to technical issues at the time of data collection. These signals were upsampled to 100 Hz using MATLAB. For upsampling, we first perform zero-padding and then use a finite impulse response, anti-aliasing filtering technique with a Kaiser window. We then normalize to account for processing gain of the window, thereby preserving the frequency content of the signal.** Gait events (heel contact and toe-off) were identified using our previously developed robust event-detection algorithm (29,30). **Briefly, the accelerations during the walking trials were recorded at 100 Hz. These signals were then zero-mean filtered to remove outliers using a median filter of order 5 and normalized by the maximum magnitude of the amplitude present. Stride information was obtained using the method described in** (29)**.** An illustration of the processed signal segment is provided in **eMethods 1** in the Supplement.

Gait parameters were calculated for each stride included: 1) Statistical features: ***signal variability*** (31) (standard deviation of accelerations amplitudes); ***symmetry*** and ***similarity*** - skewness and kurtosis of signal amplitude, cross-correlations between axes.) 2) Signal frequency features (peak frequency (32), centroid frequency, bandwidth, ***smoothness*** of walking (20,30) - harmonic ratio), (3 Time-frequency feature (wavelet entropy) (4 Information-theoretic features (***regularity*** of walking (22) - entropy rate, lempel-ziv complexity). Previous studies have shown that these spatiotemporal measures are impacted due to age in all three directions of walking - mediolateral (ML), vertical (V) and anterior- posterior (AP) (33,34), hence all of them were analyzed in detail. **MATLAB 2019a has been used for signal processing and extracting accelerometry measures.**

Gait measures from Instrumented walkway

Gait speed was derived from walks over a 4 m long instrumented walkway (**eFigure 1B** in the Supplement) (Zeno Walkway, Zenometrics, Peekskill, NY) **in laboratory conditions. The subject began walking approximately two meters from the start of the mat and stopped approximately two meters past the end of the mat and completed six passes at their self-selected usual speed. The reported gait speed is the subject's average gait speed over six passes. Gait variability measures i.e., coefficient of variation of step length, step time and stride width were calculated from the recorded measures of the footfalls (35,36). During these six passes, 24 or more steps are generally available for extraction of these measures. Previous research by our group has shown these number of steps to be sufficient for reliability of variability measures** (37)**.** PKMAS software (Protokinetics, Havertown, PA) was used for calculating the measures from footfall time and length recordings. Besides these measures, walk ratio (step length/cadence) was also computed. The walk ratio considered an index of neuro-motor control (38).

Collecting health characteristics

Self-reported walking confidence score, fall history and executive function constitute health characteristics that are known to impact life space score. Modified Gait Efficacy Scale is a selfreport measure of an individual's confidence in walking in different circumstances. It includes ten questions about confidence in safely walking on even and uneven surfaces, safely negotiating curbs and stairs, and more. A subject can respond anywhere from 1 (no confidence) to 10 (complete confidence) for each item and there are ten items. Scores range from 10 to 100 (39). For fall history, each subject reported first whether they are afraid of falling. In addition, the participant reported if they had fallen more than once in the past year. Falls are associated with a limited life space (26). Trail making tests are a general measure of executive functioning. Trails A and B components considered an indicator of visual search and perceptual processing speed, especially related to cognitive flexibility (40). Both Trails A and Trails B consist of 25 circles distributed over the page. Subjects are asked to complete each of the trail making tests as quickly as possible, maximum allowable time being 90s and 300s, respectively. The variables including gait variables from two modalities, demographics and health characteristics used in the analyses, are summarized in **eFigure 1C-1E** in the Supplement.

LSA predictive modeling and variable importance analysis

Random Forest model (41) was developed to investigate the predictability of LSA from the gait measures. Included in the model were the selected gait variables, demographics (age, gender) and cognitive function (Trails A). **A reduced set of gait variables were included in the model. The method of reducing the number of variables used partial spearman correlations of the gait quality variables (controlled for gait speed) with LSA with a significance level of p<0.1 for further evaluation. To avoid multicollinearity effects in gait variables, a correlation matrix of the selected variables was then constructed. If there are a group of gait variables that were moderately or highly correlated, one of the groups was chosen to be in the model. If a variable is correlated only with its variants in different direction, then the variable with higher correlation coefficient is chosen, if the coefficient value is same, then ML direction is**

given preference, since it is known to be the most affected direction in older adults (33,34)**.** **For detailed variable reduction analysis, see eMethods 2 in the Supplement.** The random forest method was chosen for the analysis because it is robust to outliers and to non-linearities in the variable distributions. Further, bootstrapping and parallel decision trees in random forest model control for over-fitting. **We used SHapley Additive exPlanation (SHAP) method to determine importance of gait features contributing to LSA. SHAP computes marginal contribution of each variable in predicting LSA, considering all possible permutations of variables in the model** (42)**.** Thus, the model investigates how gait measures compared to other factors in predicting LSA. The dataset was split into a training set (70%) and testing set (remaining 30%). A 3-fold cross validation on the training set was used for parameter tuning of the random forest. **Python 3.7 software, specifically sklearn machine learning library, was used for data modelling. We iteratively found the most appropriate set of parameters that resulted in minimum mean squared error. The parameter settings that we tested are given in eTable 1** in the supplement. The parameters indicated by the tuned model were then used. The 5-fold cross-validation mean squared error and the percentage explained variance on the data is reported for two models – first, using only gait variables and second, using gait and additional variables.

Clustering participants based on their gait quality

A Gaussian mixture model-based clustering algorithm was built to investigate **participant groups** with similar gait characteristics. We included the uncorrelated gait performance variables. In this unsupervised method, we used the Bayesian information criterion to evaluate the appropriate number of clusters. **Equation (1) and (2) illustrate the algorithm.**

$$\mathbf{L = log}\left\{\prod_{i=1}^{n}\sum_{k=1}^{K}\pi_k\, N(x_{i,}\mu_k, \Sigma_k)\right\} \qquad \mathbf{(1)}$$

For n observations, $x_{i=1,2,\ldots n}$ assumed to be independent and identically distributed, given K clusters, the iterative algorithm maximizes the log-likelihood, L of probability of an observation belonging to k^{th} cluster. The mean vector and covariance matrix of the k^{th} gaussian mixture component are represented as μ_k and $\sum_k$; π_k is the mixture probability of an observation belonging to cluster k. We varied the number of clusters, K from 1 to 10. The K corresponding to minimum Bayesian information criterion, BIC was selected.

$$\mathbf{BIC = p \log n - 2(L)} \tag{2}$$

In the above equation, BIC, p is the number of parameters to be estimated. Python 3.7 sklearn library using default parameter settings has been used for Gaussian mixture modeling.

After selection of number of clusters, subject datapoints with automated labels are visualized in a 3-dimensional plane constructed using the first three components from Principal Component Analysis. The clusters of participants that were obtained were examined for differences in gait quality and in all other measures not used in the model i.e., LSA score, gait efficacy, cognitive and fall history variables. The significance in difference was computed using an independent t-test and Chi-square tests, adjusting p-value for multiple comparisons using **Bonferroni correction ($p_{adjusted}$ = 1/14 ~ 0.004) for variables in model and for variables not in model.** A dataflow diagram illustrating the overall steps in the analysis is indicated in **eMethods 3** in the supplement.

Results

Community-dwelling older adults participated (N=232, mean age 77.54 (STD 6.56), 152 females, 89% whites, 44% had more than a high school education). LSA scores ranged from 34 to 120, with a mean of 74.66 (STD 18.57). The distribution of LSA scores of within and out-of-home mobility is shown in **eTable 2** in the Supplement. These community-dwelling older adults had less variable within-home mobility trends compared to their mobility behaviors in the neighborhood and beyond.

Gait quality and LSA association analysis

Associations between laboratory-measured gait quality and community mobility assessed using are shown in **Table 1**. Statistically significant correlation values (p<.10 ranged between -0.22 to 0.26. A detailed association analysis of all variables assessed is presented in **eTable 3-5** in the supplement. An **inter-variable correlation heatmap is also presented in eMethods 2 of the Supplement.**

Gait Quality based Predictive Modelling for LSA

Controlling for gait speed and multicollinearity, eight gait variables were selected for building a random forest based predictive model (**Table 2**). **After 3-fold cross-validation, the parameters for the random forest model were selected as maximum depth of 10, maximum features = 'sqrt', minimum samples at leaf = 2, Minimum samples split = 2, and number of estimators = 1050. The random forest model to assess variable importance in LSA prediction had a 5-fold cross-validation root-mean-squared-error of 18.17 and an explained variance of 4%. A second model that also included age, gender, gait efficacy, and Trails A resulted in a 5-fold cross-validation root mean squared error of 17.77 and a 10% explained variance in prediction of LSA.** Gait quality variables of Standard deviation ML, cross-correlation AP-V, Harmonic Ratio AP and Peak frequency V ranked in the top five variables for both models, with little change in prediction errors (**Figure 1A-B and 1C-D**). Age and gender had relatively low importance compared to gait and cognitive measures. In addition to showing how much each predictor contributes, SHAP plots show the positive and negative relationship for each variable. The SHAP plots indicate global interpretability (**Figure 1A and 1C**), to understand the contribution of each variable as well as local interpretability (**Figure 1B** and **1D**), where each observation receives its own set of values.

Clustering of participants and their gait characteristics

A Gaussian mixture model implemented using only gait variables indicated two groups (**Figure 2A**) of older adults (better gait quality (N=189) and poorer gait quality (N=43)). The better gait quality group was defined by a greater: cross-correlation AP-V, harmonic ratio AP, peak frequency V, and gait speed and a lower: mean step time CoV, entropy rate V, and cross-correlation ML-AP compared to the group with poorer gait quality, $p < 0.004$ (**Table 1**, **Figure 2B**). We also examined bivariate distributions of selected gait variables (**eFigure 2** in the Supplement). For visualizing the 8-dimensional gait data in a 3-dimensional space, principal components analysis was used. The datapoints here are labelled per the clusters identified by GMM (**Figure 2C**). The better gait defined by these three principal components are clustered, whereas the poorer functioning subject are dispersed outside this range of components. The primary contributors to each of the principal axes (indicating maximum variance) are gait speed (Principal Component-1), step time variability (Principal Component-2) and peak spectral frequency (Principal Component-3) (**Figure 3**). We compared the health and demographic characteristics between the two groups indicated by gait quality of older adults. We found that the real- life achieved mobility i.e., LSA and walking confidence measured as the gait efficacy were greater for the group with better gait quality ($p<0.004$ for each) (**Table 1**). No other between group differences with respect to cognitive and fall history variables were noted.

Discussion

Gait quality measures were primary predictors of high LSA, even when age, speed of processing (Trails A), and gait efficacy were included. We found a combination of greater walking speed, low step time variation, greater smoothness with more symmetric but a lower gait regularity are associated with a better LSA i.e., the achieved mobility of older adults.

Analyzing the acceleration features in both time and frequency domains is important as we learn more about the gait characteristics quantifying ’how we walk’. A lower step-time coefficient of variation (CoV) as obtained by the instrumented walkway may be a desirable characteristic as it relates to a better LSA, but, from the analysis of trunk acceleration, a greater standard deviation of walking i.e., a greater spread of amplitudes was related to high LSA. This insinuates that step-time CoV maybe interpreted as variability in the lower-extremities and the standard deviation of acceleration signal could be interpreted as adaptability, an ability to shift between greater and lesser variability; adaptability indeed being a key characteristic to navigate in the outdoor community. Association of high peak frequency of the signal, specifically in the V direction to a high LSA aligns with prior studies where low amplitude of the dominant frequency was shown to be associated with increased fall risk (33) and was found to differentiate patients with Parkinson’s disease from healthy controls (43). Harmonic ratios specifically in AP direction is an important variable in our predictive modelling approach. This directional measure differentiates young and old walkers (44), Parkinson’s affected patients from healthy controls (30,45) and even identifies subjects with a high risk of falling (46).

As for gait regularity (which is an information-theoretic feature), contrary to our expectations, we found its lower value in V direction to be associated with higher mobility. In some studies, an increased entropy in V direction has been found to associate with increased fall risk (47). Entropy V also differentiates walk-only and dual task walking (22). One possible explanation is that a high entropy rate also means that an individual is restricting his degree of freedom of motion and is walking en bloc, thus a lower entropy may be a desirable quality - meaning greater inter-segment degrees of freedom important for effective mobility in everyday life. It is important to note, that after controlling for gait speed, most gait variables that add unique yet complimentary information for understanding mobility in older adults are the ones derived from trunk acceleration, and not from the instrumented walkway. **"Individual associations are statistically significant but small, ranging from 0.11 to 0.26. High correlations for bivariate relations were not expected for any particular aspects of the quality with self-reported mobility. The LSA is influenced by potentially many factors beyond walking ability such as risk-taking, necessity, match between person and environment accessibility, comfort and interest. However, the associations found in this study may well indicate important aspects as well. How a person walks and their confidence in walking ability for conditions found in navigating the environment could be important towards addressing improvements through rehabilitation. Our non-linear data-driven approach, i.e. Random forest and clustering analysis, led us to consider not just individual gait quality factors but also combinations that could affect LSA."** With these gait quality measures we could identify two groups with distinct gait qualities. One of the groups identified using unsupervised classification was found to not only have a better gait quality (faster gait speed, less step time variability, higher peak frequency amplitudes and high cross correlation in AP-V direction) but also was found to have a better LSA and more gait efficacy, even though LSA and gait efficacy were not included in the model; these results being well matched to our Spearman correlation findings (**Table 1**) and to the Random forest regressor analysis (**Figure 1**). Some studies have found a difference or change of 5 or more points in LSA to be clinically important (48,49). **Thus, our finding of a difference**

in the LSA of 10 points may help in identifying the older adults that are at more risk for mobility related disability and in informing early physical therapy interventions.

Considering daily walking, it is essential to monitor walking 'quality' besides the quantity of daily walking. So far, 'number of steps taken' has been the primary focus of wearable activity-monitoring devices but step count can be deceiving since older subjects with functional limitations likely take a greater number of steps to cover the same distance and may appear to be more active than other healthier subjects, when in fact this may not be the case (50). The time-frequency measures we extract during the laboratory can also be extended as potential measures for real-life gait assessment.

There are some limitations to the study. Potentially important contributors such as daily activity, environment, economic stature, marital status, education and mental health that may impact a person's mobility in the community (6) were not able to be included in the study. **Another potential limitation is that our measures were performed in a laboratory environment, thus, indicating gait capacity rather than gait of daily life. One technical limitation is that the assessment is restricted to three linear accelerations i.e., Mediolateral, Vertical and Anterior-Posterior and did not include rotation information from gyroscopes. Future studies should consider using gyroscope information which may prove useful in examining gait quality during curve path and challenge task walking in relation to LSA.** Though daily-activity behavior monitoring via accelerometery has been done in recent studies, measurement of quality remains an open research question. A combination of information from both LSA (a self-reported, validated, reliable and quick to compute measure) along with other emerging wearable technology like global positioning system, may inform us better about community mobility.

In summary, we examined the associations between multiple gait measures and self-reported community mobility in older adults. Among older adults, gait quality measures along with gait efficacy and speed of processing informed more about mobility than age and gender. Using an unsupervised machine learning approach to classify participants based on gait quality, life-space and gait efficacy, we further established the importance of gait quality measures.

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Author Contributions

A.S., A.L.R., E.S., M.S.R. and J.V. designed the research question and formulated the hypothesis. J.S.B., A.L.R., J.V. and E.S. designed the main PRIMA study and data acquisition protocols (They are the PI and co-PI). L.C. performed the data acquisition. A.S., A.L.R., E.S., M.S.R. and J.V. conceptualized the methods for data analysis. A.S. performed the analysis. A.S., A.L.R., E.S., J.V., and L.C. contributed to interpretation of results. All the authors contributed to drafting and revising the manuscript.

Conflicts of interest

None reported

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Table 1. Correlations of demographic, health and gait variables to Life Space Assessment, *p*<0.1

Gait Variable	Mean ± STD[a]	Spearman correlation with LSA[b], ρ
Health Characteristics		
*Age (years	77.54 ± 6.56	-0.22
*Gender	65% females	-0.17
*Gait Efficacy	85.41 ± 13.36	0.23
*Trails A[c] (s)	33.56 ± 13.14	-0.19
*Trails B[d] (s)	85.30 ± 46.23	-0.15
Gait Quality: Trunk Acceleration		
Statistical features		
*Standard deviation ML[e]	0.13 ± 0.05	0.11
**Standard deviation AP[f]	0.18 ± 0.07	0.11
*Kurtosis V[g]	5.33 ± 6.34	-0.13
*Cross-correlation ML-AP	0.20 ± 0.09	-0.13
*Cross-correlation AP-V	0.55 ± 0.16	0.15
Frequency features		
*Peak frequency V	1.70 ± 0.87	0.16
**Harmonic ratio ML	0.59 ± 0.27	0.11
**Harmonic ratio AP	2.82 ± 0.78	0.12
Info-theoretic features		
**Entropy rate V	0.84 ± 0.08	-0.12
**Entropy rate AP	0.86 ± 0.06	-0.13
*Lempel-Ziv complexity V	0.46 ± 0.09	0.16

**Lempel-Ziv complexity AP	0.43 ± 0.09	0.13
Gait Quality: Instrumented Walkway		
**Step time CoV[h]	3.96 ± 1.51	-0.11
*Gait Speed (m/s)	1.08 ± 0.16	0.26

Notes.

[a]Standard Deviation

[b]Life Space Assessment

[c]Time taken to do trail making test A

[d]Time taken to do trail making test B

[e]Medio-lateral axis

[f]Anterior-Posterior axis

[g]Vertical Axis

[h]Coefficient of variation

*statistically significant, $p<0.05$, ** statistically significant, $p<0.1$

Table 2. Health and Gait quality measures selected to model life-space mobility; along with characteristics of two groups that were identified using unsupervised Gaussian mixture model clustering

Variable	Total Sample N=232	Group 1 N=189 (Better gait)	Group 2 N=43 *(Poorer gait)*
Health Characteristics			
Age (years)	77.54 ± 6.56	77.57 ± 6.55	77.4 ± 6.69
*Body Mass Index (kg/m^2)	28.50 ± 5.75	28.07 ± 5.51	30.41 ± 6.42
Female	152 (65%)	118 (62.43%)	34 (79.07%)
**Gait efficacy	85.41 ± 13.36	86.86 ± 12.58	79.05 ± 14.93
Fear of Falling[a]	96 (40%)	75 (39.68%)	21 (48.84%)
Recurrent faller[b]	25 (10.77%)	20 (10.58%)	5 (11.63%)
Trails A[c] (s)	33.56 ± 13.14	33.19 ± 13.33	35.19 ± 12.30
Trails B[d] (s)	85.30 ± 46.23	82.76 ± 40.98	96.46 ± 63.89
*Life Space Assessment	74.66 ± 18.57	76.41 ± 18.31	66.95 ± 17.94
Gait quality: Trunk acceleration			
Statistical features			
**Cross-correlation ML[e]-AP[f] (signal symmetry and similarity)	0.20 ± 0.09	0.19 ± 0.08	0.23 ± 0.11
**Cross-correlation AP-V[g] (signal symmetry and similarity)	0.55 ± 0.16	0.58 ± 0.13	0.40 ± 0.19
Standard deviation ML (signal amplitude variability)	0.13 ± 0.05	0.13 ± 0.05	0.13 ± 0.05
Frequency features			
**Harmonic Ratio AP (smoothness of walking)	2.82 ± 0.78	2.94 ± 0.75	2.30 ± 0.71

**Peak frequency V (power and dominant frequency)	1.70 ± 0.87	1.86 ± 0.18	0.97 ± 1.84
Information-theoretic features			
**Entropy rate V (regularity of walking)	0.84 ± 0.08	0.83 ± 0.08	0.87 ± 0.10
Gait quality: Instrumented Walkway			
**Step time CoV[h] (variability of lower extremities)	3.96 ± 1.51	3.70 ± 1.09	5.09 ± 2.37
**Gait Speed (m/s) (speed of walking)	1.08 ± 0.16	1.09 ± 0.16	1.00 ± 0.16

Notes.

[a]Number of people (percentage) who are afraid of falling

[b]Number of people (percentage) who have fallen more than once in the past one-year

[c]Time taken to do trail making test A

[d]Time taken to do trail making test B

[e]Medio-lateral axis

[f]Anterior-Posterior axis

[g]Vertical Axis

[h]Coefficient of variation

* statistically different, p< .05 **statistically different after adjusting for multiple comparisons, ***p*<.004**