



Measuring Walking Quality Through iPhone Mobility Metrics

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Overview

Using the motion sensors built into iPhone 8 and later, iOS 14 provides Mobility Metrics that are important for your health. This includes estimates of your walking speed, step length, double support time and walking asymmetry^{1,2} – all metrics that can be used to characterise your gait and mobility. This paper provides a detailed understanding of how these Mobility Metrics are estimated on iPhone, including their testing and validation.

Introduction

Walking is a key indicator of the status of an individual's injury,³ disability⁴ and short- and long-term health.^{5,6} Walking mobility can represent the ability to age with independence,⁷ and it is affected by a variety of health conditions, including muscular degeneration,⁸ neurological disease^{9,10} and cardiopulmonary fitness.¹¹ A simple way that health professionals measure an individual's mobility is by observing them walking.^{12,13} Walking requires a suite of complex components that are co-ordinated across multiple physiological systems, and a single failure of any element may indicate progression of a disease or an increased risk of injury.

Measurement of walking performance is often used to assess an individual's health status,¹⁴ track recovery from injury¹⁵ or surgery¹⁶ and monitor changes that occur with ageing.¹⁷ Some commonly used walking performance measurements are walking speed, step length, double support time and walking asymmetry.

- Walking speed, and how it changes over time, is closely related to clinically meaningful health outcomes.^{4,18} Measured walking speed is frequently used to track recovery from acute health events, such as a joint replacement³ or stroke,¹⁹ and to monitor health changes over time, such as the progression of Parkinson's disease^{10,20} and ageing.²¹
- Step length is a marker of compromised mobility for certain types of neurologic and musculoskeletal conditions,¹⁴ and is predictive of falls and fear of falling.²² Step length decreases with age, with older adults showing reduced step length compared with younger people.^{23,24} Shortening step length is an important consideration as we age,²⁵ and early exercise interventions may provide a way to maintain independence.^{26,27}
- Double support time is the proportion of time that both feet are touching the ground during walking. It increases when a person has an injury¹⁶ or dysfunction, both in terms of absolute time and as a percentage of each gait cycle.²⁸ An increase in double support time has been related to a rise in an individual's fear of falling,²² while lower double support times are correlated with improved walking stability and a lower risk of falling.²⁹
- Walking asymmetry emerges when a unilateral pathology or injury occurs and an individual relies on the contralateral limb when walking. An increase in walking asymmetry occurs after an injury³⁰ or due to neurodegeneration from ageing or disease.^{20,31} A decline in bilateral co-ordination between the two legs has been shown to be tied to an increased risk of falling^{32,33} and poor surgical outcomes,³⁰ and is predictive of later joint injury.^{34,35}

The Mobility Metrics estimated using iPhone 8 and later provide a passive and non-intrusive method of measuring walking quality – from young age to advanced age. In the Health app in iOS 14 and later, these estimated Mobility Metrics can be viewed under Mobility (see Figure 1). This paper describes the development and validation of these Mobility Metrics on iPhone – Walking Speed, Step Length, Double Support Time and Walking Asymmetry – and provides recommendations for use.

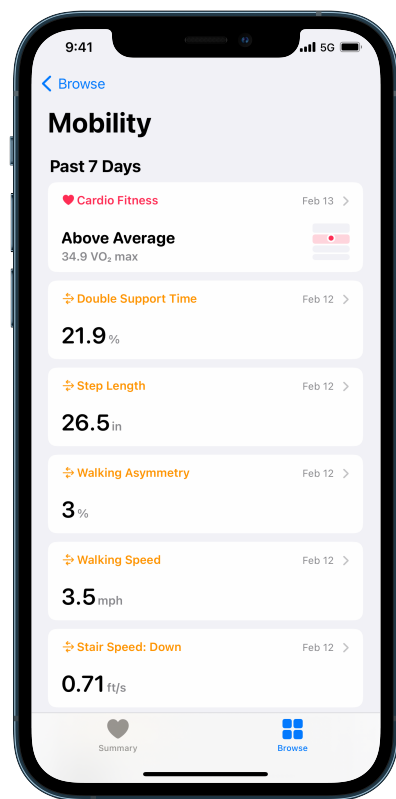


Figure 1: Mobility Metrics in the Health app in iOS 14

Development

Study Design

Data collection for the design and validation of the Mobility metrics consisted of several studies approved by an ethics board. All participants attended in-lab visits, consisting of up to two visits (at least 8 weeks apart) over the course of a year, and completed a set of walking tasks on each visit.

All participants completed invigilated overground walking tasks across an instrumented pressure mat (the ProtoKinetics Zeno™ Walkway Gait Analysis System) while carrying two iPhone devices – one on each side of their body – in different locations: on the hip (hip clip), in a front or back pocket or in a waist pouch. Participants were asked to choose where to place one device to best replicate their typical behaviour – on either the right- or the left-hand side of the body – and invigilators placed a second device in a contralateral location.

Each walking task was conducted along a 12-metre, straight-line course, with an 8-metre pressure mat placed in the centre. The pressure mat, an instrumented device that provides highly accurate heel-strike and toe-off location and timing events, was used to generate reference values for each participant's step

count, walking speed, step length, double support time and walking asymmetry. For further details on the experimental setup, see the "Data Sanity" section in the Appendix.

For participants in Cohort A, tasks included four walkovers (defined as a single walk across the pressure mat) at an instructed self-selected speed, four walkovers at an instructed slow speed and a variable number of walkovers during a fast-paced, six-minute walk test (6MWT), in which participants walked back and forth over the pressure mat as many times as possible within a six-minute period.¹² For Cohort B, participants were asked to complete several walkovers at a self-selected speed, a slow speed and a very slow speed ("as if recovering from an injury"). Participants in this cohort were recruited to simulate walking asymmetry by wearing a commercial knee brace.³⁶ The brace was locked to restrict movement to 30° flexion and 10° extension. Cohort descriptions and groupings are shown in Figure 2.

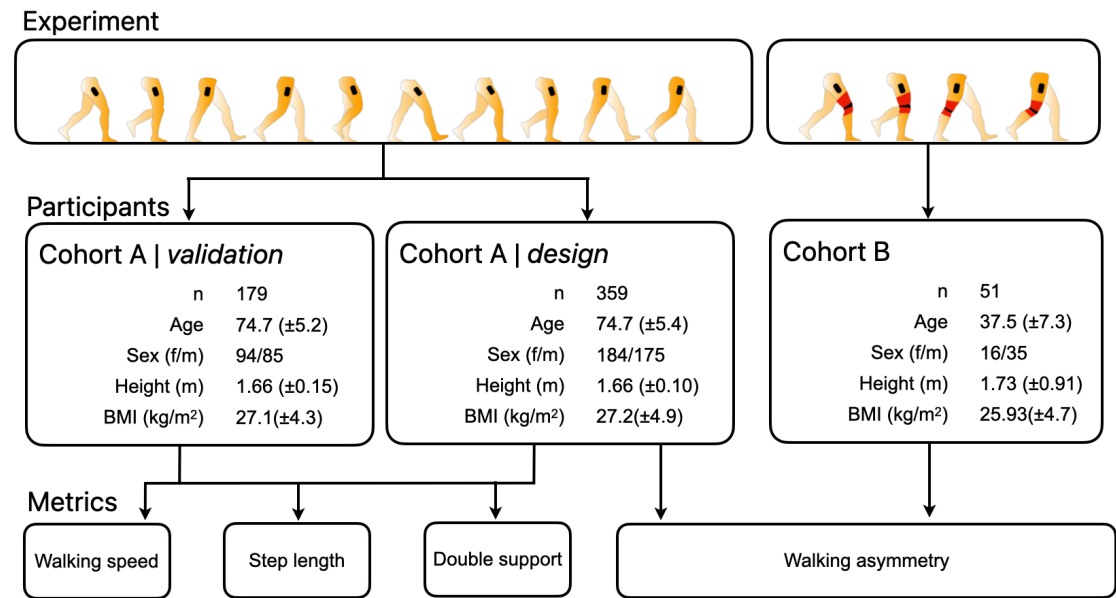


Figure 2: Study design and data aggregation. Participants from Cohort A were separated into design and validation groups for the walking speed, step length, double support time and walking asymmetry metrics; pedometer steps were validated for all Cohort A participants. Cohort B contributed to the design of the walking asymmetry metric by getting participants to wear a single-sided knee brace to simulate an asymmetric gait.

The performance of Mobility Metrics was assessed by directly comparing the values derived from the pressure mat and iPhone devices. Each iPhone in the study was considered to be an independent observer because of the multiple different device locations that were used during walkovers. A measurement recorded by one iPhone during one walking task for one participant visit is referred to as a "device visit". As an example, a participant wearing two devices during a visit would contribute two device visits. The number of straights completed on the pressure mat was multiplied by the number of device visits to produce the number of walkovers (see Figure 3). The statistical methods for assessing metric performance are described in detail in the Appendix.

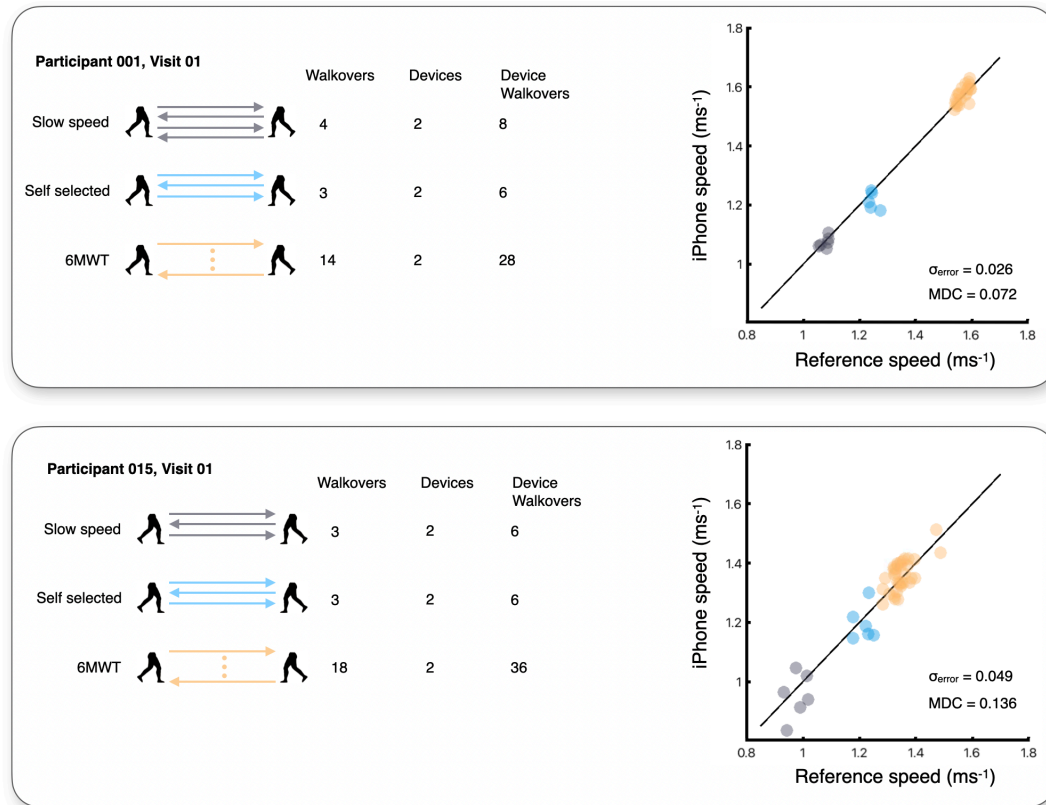


Figure 3: Example data collection and analysis. Above are two examples of data collection for Cohort A. Participants were instructed to wear two devices while completing four walkovers on the pressure mat at a slow speed, four walkovers at a self-selected speed and as many walkovers as possible in the 6MWT. Data sets for each condition were only included in analysis if they contained at least three valid walkovers at each instructed speed, and at least 10 valid walkovers in the 6MWT. Data across conditions and devices was collapsed together to calculate metric performance through estimates, such as the standard deviation of absolute error (σ_{error}) and minimal detectable change.

Population

Apple collected data for the design and validation of the Mobility Metrics across multiple studies involving two cohorts of study participants; studies were approved by an ethics board, and all participants consented to the collection and use of their data for this purpose. Cohort A was a large group of older adults who either lived in the local community or in an independent senior living community (see Table 1). Cohort B was a group of younger, able-bodied adults who were asked to wear a knee brace to elicit asymmetry (see Table 2).

Table 1. Cohort A participant characteristics

Unique participants	Design (N = 359)	Validation (N = 179)
Demographics and biometrics		
Age	74.7 (± 5.4) [64, 92]	74.7 (± 5.3) [65, 95]
Gender (female/male)	184/175	93/86
Height (metres)	1.66 (± 0.10) [1.43, 1.95]	1.66 (± 0.95) [1.44, 1.88]
BMI (kg/m ²)	26.6 (± 4.4) [17.4, 43.8]	26.9 (± 4.1) [17.9, 39.3]
Prevalence of musculoskeletal conditions	292 (81%)	142 (80%)
Prevalence of cardiovascular conditions*	259 (72%)	124 (69%)
Prevalence of neurological conditions	54 (15%)	27 (15%)
Assistive devices	13 (5%)	<10 (<5%)
Musculoskeletal conditions – number (%)		
Amputation	<10 (<5%)	<10 (<5%)
Arthritis	94 (26%)	40 (22%)
Balance disorder	64 (18%)	34 (19%)
Degenerative disc disease	27 (8%)	11 (6%)
Head or neck problems	41 (11%)	20 (11%)
Osteoarthritis	177 (49%)	88 (49%)
Rheumatoid arthritis	<10 (<5%)	<10 (<5%)
Ruptured or herniated disc	23 (6%)	18 (10%)
Joint replacement surgery	58 (16%)	29 (16%)
Other	157 (44%)	75 (42%)

*Hypertension, heart attack, heart failure, coronary artery disease, stroke, hyperlipidemia, PAD, arrhythmia.

Table 2. Cohort B participant characteristics

Design (N = 51)	
Demographics and biometrics	
Age	37.5 (± 7.3) [26, 55]
Gender (female/male)	16/35
Height (metres)	1.73 (± 0.91) [1.55, 1.89]
BMI (kg/m ²)	25.9 (± 4.7) [18.3, 42.7]

Results

Aggregate results for participants in Cohort A are shown in Table 3; these results are collapsed across design and validation data sets.

Table 3. Cohort A pressure-mat reference means, standard deviations and ranges

	Slow speed	Self-selected speed	Fast speed (6MWT)
	mean \pm SD (range)	mean \pm SD (range)	mean \pm SD (range)
Device visits	845	854	738
Walkovers	3,146	3,175	16,625
Cadence (steps \cdot minute ⁻¹)	101.60 \pm 10.50 (64.8–135.6)	114.94 \pm 9.70 (70.6–146.7)	123.35 \pm 9.56 (87.4–153.2)
Walking speed (metres \cdot second ⁻¹)	1.04 \pm 0.18 (0.47–1.57)	1.30 \pm 0.18 (0.67–1.90)	1.46 \pm 0.18 (0.65–2.16)
Step length (metres)	0.61 \pm 0.08 (0.34–0.86)	0.68 \pm 0.08 (0.45–0.88)	0.71 \pm 0.07 (0.38–0.94)
Double support time (%)	31.37 \pm 3.69 (19.56–47.08)	28.38 \pm 3.34 (18.13–39.71)	27.00 \pm 3.40 (16.03–43.36)
Overall temporal asymmetry (unitless)	1.07 \pm 0.04 (1.00–1.45)	1.06 \pm 0.03 (1.00–1.35)	1.06 \pm 0.03 (1.00–1.75)

Step Count

Pedometer step count provides an objective measurement of the number of steps that a user takes while wearing their devices. Steps detected from Apple Watch and iPhone are intelligently fused together to provide an accurate estimate of a user's all-day behaviour; the device source for the detected steps can be identified in HealthKit. In Figure 4, device visit data from Cohort A was analysed to establish the validity of iPhone step count.

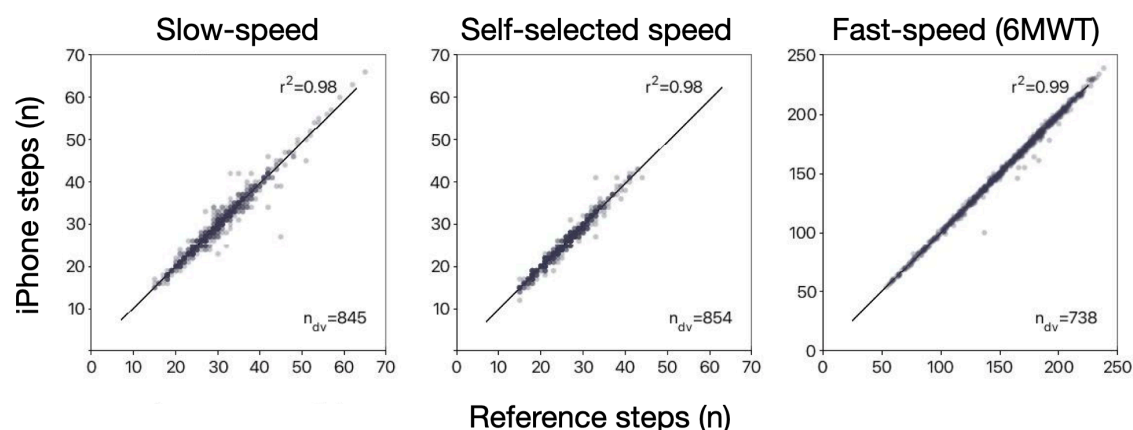


Figure 4: iPhone pedometer step-count performance. These charts show the correlation between aggregated steps registered from the pressure-mat reference and iPhone step count during slow speed (left-hand chart), self-selected (centre chart) and 6MWT (right-hand chart) walking tasks. The Pearson correlation coefficient for self-selected (1.30 \pm 0.18 metres \cdot second⁻¹), slow speed (1.04 \pm 0.18 metres \cdot second⁻¹) and 6MWT (1.46 \pm 0.18 metres \cdot second⁻¹) step counts were all above 0.96. Self-selected and slow-speed step values are aggregated from 3 or 4 walkovers, and 6MWT step values are aggregated from at least 10 walkovers.

Walking Speed

The walking speed metric represents an estimate of how quickly users walk on flat ground. It's derived from a model of the user's centre of mass. As such, the metric will be most accurate when iPhone is closely coupled to the body (such as in a pocket or attached to a belt). Also, users must have entered an up-to-date value for their height in the Health app for iOS.

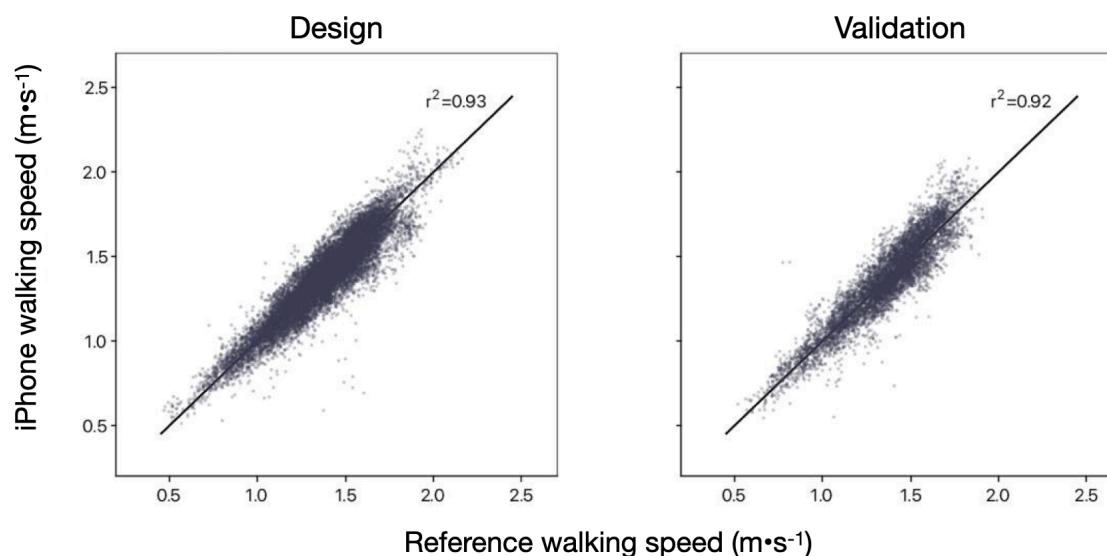


Figure 5: iPhone walking-speed performance. This shows algorithm performance for the design set (left-hand chart) and the validation set (right-hand chart) used in the development of the walking speed metric.

Table 4. Walking speed performance (mixed iPhone locations)

Metric	Description	Design	Validation
N	Participant visits (unique participants)	528 (359)	250 (179)
Walkovers	Number of walkovers on the pressure mat that were used for comparison	15,487	7,440
Validity	Standard deviation of absolute errors (σ_{error} metres · second ⁻¹)	0.09	0.15
Reliability	Comparison of pressure-mat reference and iPhone walking speed estimates ($\text{ICC}_{(A,1)}$)	0.93	0.92
Sensitivity	Minimal detectable change (metres · second ⁻¹)		
	10th percentile (most sensitive)	0.07	0.08
	50th percentile	0.13	0.14
	90th percentile (least sensitive)	0.22	0.23

Step Length

The new step length metric is an estimation of the distance between the place where one foot hits the ground and the place where the other foot hits the ground while users are walking. This metric is derived from a model of the user's height, along with step cadence and speed estimation while users are walking steadily on flat ground.

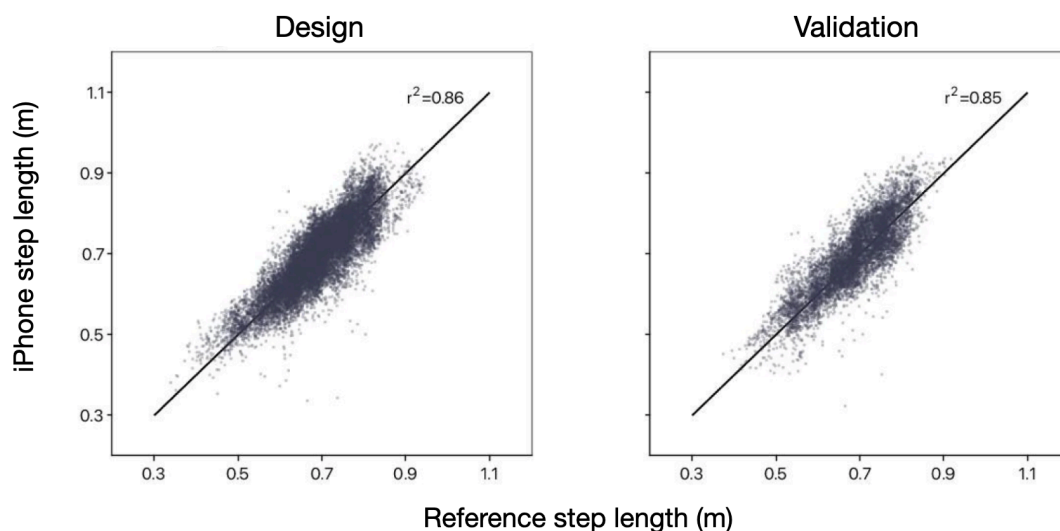


Figure 6: iPhone step-length performance. This shows algorithm performance for the design set (left-hand chart) and the validation set (right-hand chart) used in the development of step length metric.

Table 5. Step length performance (mixed iPhone locations)

Metric	Description	Design	Validation
<i>N</i>	Participant visits (unique participants)	528 (359)	250 (179)
Walkovers	Number of walkovers on the pressure mat that were used for comparison	15,487	7,440
Validity	Standard deviation of absolute errors (σ_{error} metres)	0.05	0.05
Reliability	Comparison of pressure-mat reference and iPhone step length estimates ($\text{ICC}_{(A,1)}$)	0.85	0.84
Sensitivity	Minimal detectable change (metres)		
	10th percentile (most sensitive)	0.04	0.04
	50th percentile	0.09	0.07
	90th percentile (least sensitive)	0.14	0.12

Double Support Time

The double support time metric provides a measurement of the percentage of the gait cycle – from heel strike on one foot to heel strike on the contralateral foot – that a user spends on two feet (double support). The metric can range from values of 0 per cent (for example, while running, individuals lunge from foot to foot with no overlap of two feet on the ground) to 100 per cent (for example, while standing still or during extreme shuffling, both feet are always on the ground). Typical walking behaviour ranges between 20 and 40 per cent, with lower values indicating better balance.

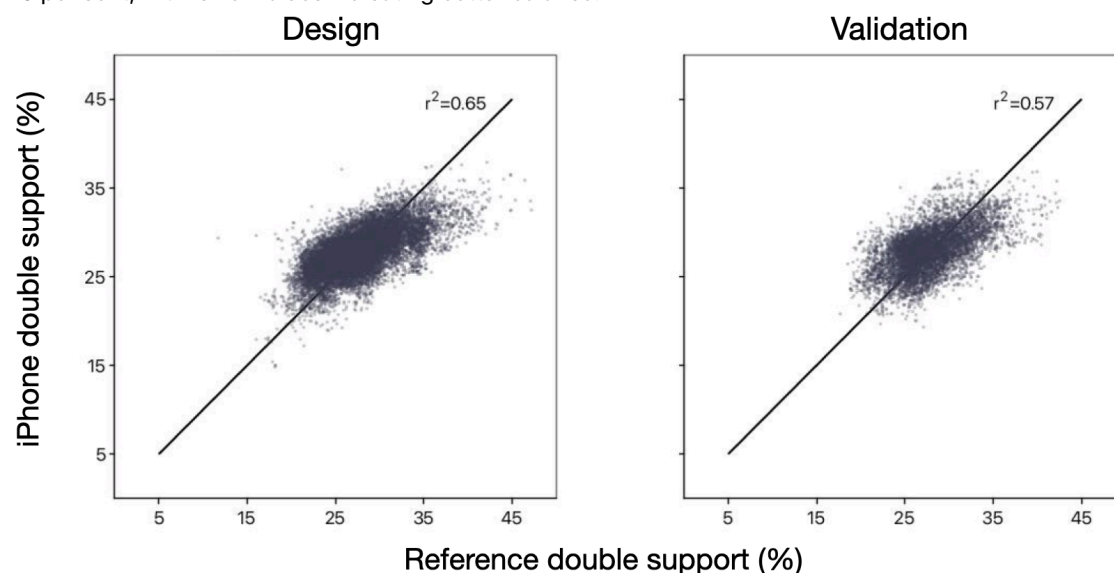


Figure 7: iPhone double support time performance. This shows algorithm performance for the design set (left-hand chart) and the validation set (right-hand chart) used in the development of the double support time metric.

Table 6. Double support time performance (mixed iPhone locations)

Metric	Description	Design	Validation
N	Participant visits (unique participants)	528 (359)	250 (179)
Walkovers	Number of walkovers on the pressure mat that were used for comparison	15,487	7,440
Validity	Standard deviation of absolute errors (σ_{error} %)	2.91	2.95
Reliability	Comparison of pressure-mat reference and iPhone double support time estimates ($\text{ICC}_{(A,1)}$)	0.59	0.53
Sensitivity	Minimal detectable change (%)		
	10th percentile (most sensitive)	2.06	2.12
	50th percentile	3.17	3.18
	90th percentile (least sensitive)	5.06	4.51

Walking Asymmetry

The walking asymmetry metric provides an estimate of the percentage of time that asymmetric steps are detected within a walking bout. The metric doesn't provide a classification of asymmetry severity, but rather the percentage of time that an asymmetric gait is detected. It can range from 0 per cent (indicating that all walking steps within an observed walking bout were estimated to be symmetrical) to 100 per cent (indicating that all walking steps observed were asymmetric).

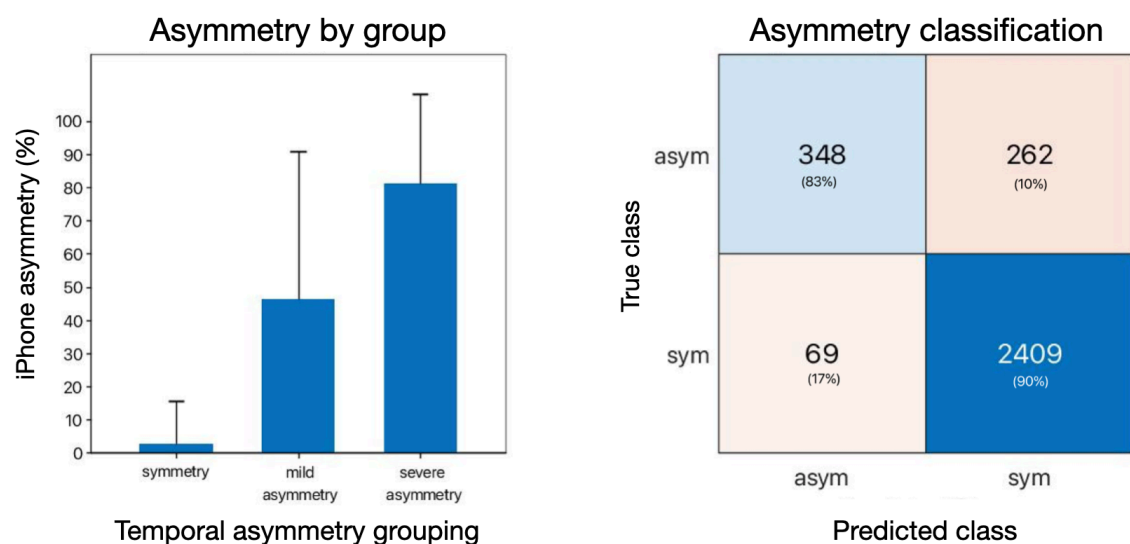


Figure 8: iPhone walking asymmetry. The left-hand chart shows the mean and standard deviation of iPhone walking asymmetry estimates, where reference values classified device visits as having symmetry, mild asymmetry or severe asymmetry. The right-hand chart shows the confusion matrix for the asymmetry classification, where iPhone asymmetry of 35 per cent showed a positive predictive rate of 84.2 per cent (348 true positives from 417 asymmetry-classified device visits) and a false negative rate of 2.78 per cent (69 false positives from 2,671 symmetry-classified device visits).

Table 7. Asymmetry classification from values of overall temporal symmetry

	Asymmetry		
	Symmetry	Mild asymmetry	Severe asymmetry
Overall temporal symmetry	1.0-1.1	1.1-1.5	>1.5
Participants	392	125	21
Device visits (number)	2,478	516	94

Discussion

The Mobility Metrics described in this paper provide consumers, researchers and healthcare providers with a mechanism for assessing mobility during day-to-day life outside the clinic. Previous advocacy for gait assessment focused on cost-benefit analysis, and the recommended use of gait analysis is limited to certain conditions based on cost and availability of testing³⁷; availability of these metrics on a widely adopted consumer platform, such as iPhone, may expand the range of recommended applications. Other research has previously demonstrated the usefulness of inertial sensors, such as those found in wearable devices, in augmenting clinical exams by providing objective measures of impairment, monitoring disease progression and evaluating response to treatments.³⁸

The availability and application of these metrics in clinical or research settings may provide an insight into clinically reliable and meaningful thresholds and allow greater application of known thresholds. For example, a 10cm/s decrease in walking speed within a year has been associated with an increased risk of falls in older populations.³⁹ Short-term changes in walking speed in older adults with heart failure have been shown to be prognostic of longer-term outcomes.⁴⁰ And walking speed, step length and double support time have been used to objectively measure treatment-mediated improvements in walking for individuals with multiple sclerosis.⁴¹ Other applications already exist and more will almost certainly be discovered, as exploration may have been hindered by a lack of available, relevant data in the past.

The development and validation of the Mobility Metrics are limited in several ways. First, due to a scarcity of individuals with an asymmetric gait, asymmetry was induced artificially using a knee brace in the Cohort B study. Although this method has been shown to reliably induce asymmetric walking,³⁶ the mechanics of this type of asymmetry could differ substantially from asymmetry due to, for example, neurodegenerative disease⁴² or prosthetics.⁴³ Furthermore, the study population didn't span all adult ages and was limited to individuals residing in Santa Clara Valley, California, USA. Although walking capacity can differ across demographic categories, such as race or ethnicity,⁴⁴ it's widely accepted that bipedal pendular walking doesn't vary substantially once adult age has been reached, unless a person's gait becomes substantially impaired.⁴⁵ Therefore, the metrics outlined here should be accurate for tracking normal walking across a person's lifespan, but they'll need to be validated further for more specific populations.

In this paper, we describe the performance of Mobility Metrics on iPhone by aligning each detected step and gait cycle against a gold-standard pressure mat reference. In HealthKit, these metrics are aggregated into time bouts of valid overground walking. For this reason, the Mobility Metrics described here aren't available all day (for example, they won't be present when users are running or are hiking uphill, as shown in Figure 9). Instead, they're pre-filtered to provide the most accurate output.

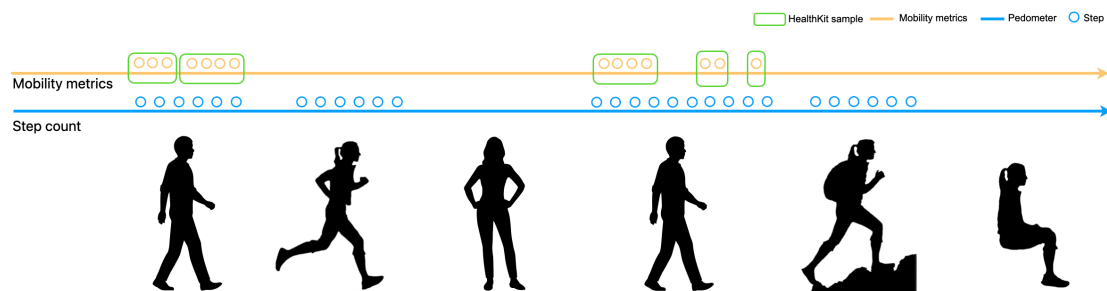


Figure 9: Schematic of HealthKit metric availability. Mobility Metrics are reported in HealthKit during periods of flat, overground walking, while pedometer steps are reported during any activity in which steps can be reliably estimated. Because the metrics are pre-filtered to periods when walking quality is best estimated, the availability of the metrics may not overlap with pedometer step counts.

The metrics are derived from a biomechanical model of walking that depends on an accurate estimate of leg length, which is estimated from the height entered by the user. Users should enter their height in the Health app for iOS to receive the most accurate estimates. No other calibration is required. Additionally, the availability of measurements will largely depend on the user's interaction with iPhone. Given the need for a tight coupling of a device to a user's centre of mass, individuals who carry iPhone in a location that provides a good signal (for example, in a pocket close to the hip) will receive more frequent estimates than users who primarily carry iPhone in another location (for example, in their hand, in a rucksack or in a handbag). For users who have received at least one walking bout estimate, on average, over 80 per cent of them will receive at least five estimates of their Mobility Metrics per day. The metrics won't be available if users have turned on Wheelchair mode in the Health app for iOS.

Conclusions

Mobility Metrics on iPhone allow users to assess their functional mobility opportunistically and passively. Tracking these metrics longitudinally over time, in a non-intrusive way, provides an objective measurement of all-day mobility that can augment specialised functional tests and clinical questionnaires. These metrics provide users, researchers and healthcare providers with a new tool for tracking and quantifying functional mobility.

Appendix

Data Sanity

Start and end times for each walkover were defined from the first heel strike recorded on the pressure mat to the final toe-off time recorded on the pressure mat. The reference values from the pressure mat were precisely time-aligned with iPhone estimates for step count (see the blue line in Figure 10) and Mobility Metrics (see the orange line in Figure 10), and direct comparisons were made for each walkover.

Step counts were estimated for participant visits containing at least three valid walkovers for the self-selected and slow-speed tasks, and 10 valid walkovers for the 6MWT task. Walkovers were rejected if participants walked off the pressure-sensitive portion of the mat or if foot contacts weren't registered correctly (for example, due to partial foot landing on the pressure-sensitive mat).

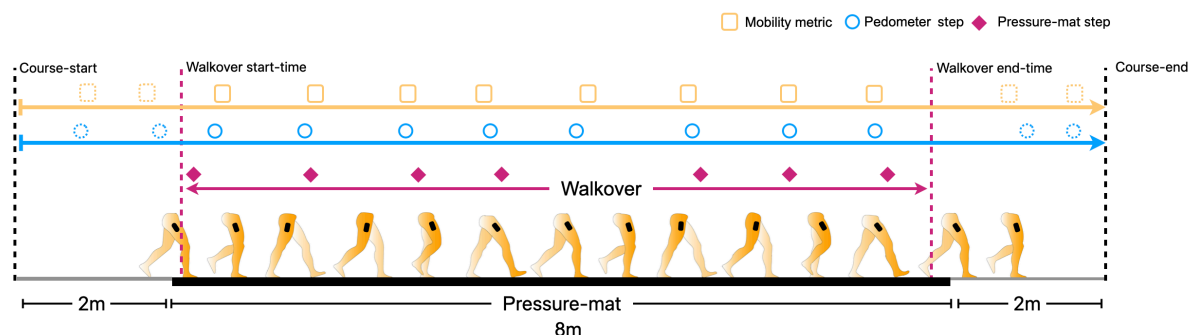


Figure 10: Experimental setup for comparing pressure mat to iPhone Mobility Metrics and step counter. Participants walked on a pressure mat (8 metres) that registers foot contact time and displacement. For each walkover, the number of foot contacts, foot-contact times and foot-contact displacements were used to determine step count, walking speed, step length and double support time on the pressure mat. The first and last registered foot-contact times on the pressure mat determined the walkover start and end times (purple line), which were precisely aligned with the iOS pedometer and Mobility Metrics.

Statistical Methods

Continuous Metrics

Time-synchronised iPhone and reference step counts were aggregated for each walking task and compared using the Pearson correlation coefficient (r^2).

For the development of the walking speed, step length and double support time metrics, device visits gathered from Cohort A were split into design and validation data sets, and the design set was used to develop each metric's algorithm. Algorithm performance for the three metrics was determined by comparing their estimates with the reference values from the pressure mat. Metric validity was assessed using the standard deviation of absolute errors between reference and iPhone estimate pairs. Metric reliability was assessed using the Pearson correlation coefficient (r^2) and inter-rater intraclass correlation coefficient ($ICC_{(A,1)}$). Sensitivity was assessed using minimal detectable change⁴⁶ of each device visit, with percentile distributions being reported.

Classification Metrics

For the development of walking asymmetry, device visit data was collated from both Cohort A and Cohort B. Each set of device visits was used to calculate overall temporal symmetry ratio⁴⁷ and classify reference device visits into "symmetry", "mild asymmetry" and "severe asymmetry" walking groups. For the device visits in each group, the mean and standard deviation of iPhone walking asymmetry were calculated. A receiver operating characteristic (ROC) analysis was then used to evaluate the ability of iPhone walking asymmetry to categorise participants successfully as symmetrical or asymmetrical walkers.

Asymmetry Definition

For each participant device visit, symmetry was calculated as an overall temporal symmetry ratio⁴⁷:

$$SSR = \frac{swing_{time}}{stance_{time}} * 100 \quad (1.1)$$

$$symmetry = \frac{max(SSR_{left}, SSR_{right})}{min(SSR_{left}, SSR_{right})} \quad (1.2)$$

where $swing_{time}$ and $stance_{time}$ are the mean swing and stance times of strides on the pressure mat being calculated for the left- (SSR_{left}) and right-hand (SSR_{right}) sides. The definition of symmetry uses functions $max(SSR_{left}, SSR_{right})$ and $min(SSR_{left}, SSR_{right})$ in the numerator and denominator, respectively, to remove sidedness from the interpretation. Participants with an overall temporal symmetry ratio between 1.0 and 1.1 were considered to have a symmetrical gait; a temporal symmetry ratio between 1.1 and 1.5 was considered to be a gait with mild asymmetry, and a ratio greater than 1.5 was recorded as a gait with severe asymmetry.⁴⁷ A summary of the symmetry cut-offs for the pressure mat, including the number of device visits for each of the three types of walking asymmetry (symmetry, mild asymmetry and severe asymmetry) is found in Table 7.

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