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Gait speed assessed by a 4-m walk test is not representative of daily-life gait speed in community-dwelling adults

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ABSTRACT

Objectives: Standardized tests of gait speed are regarded as being of clinical value, but they are typically performed under optimal conditions, and may not reflect daily-life gait behavior. The aim of this study was to compare 4-m gait speed to the distribution of daily-life gait speed.

Study design: The cross-sectional Grey Power cohort included 254 community-dwelling participants aged 18 years or more.

Main outcome measures: Pearson's correlations were used to compare gait speed assessed using a timed 4-m walk test at preferred pace, and daily-life gait speed obtained from tri-axial lower-back accelerometer data over seven consecutive days.

Results: Participants (median age 66.7 years [IQR 59.4–72.5], 65.7% female) had a mean 4-m gait speed of 1.43 m/s (SD 0.21), and a mean 50th percentile of daily-life gait speed of 0.90 m/s (SD 0.23). Ninety-six percent had a bimodal distribution of daily-life gait speed, with a mean 1st peak of 0.61 m/s (SD 0.15) and 2nd peak of 1.26 m/s (SD 0.23). The percentile of the daily-life distribution that corresponded best with the individual 4-m gait speed had a median value of 91.2 (IQR 75.4–98.6). The 4-m gait speed was very weakly correlated to the 1st and 2nd peak ($r = 0.005$, $p = 0.936$ and $r = 0.181$, $p = 0.004$), and the daily-life gait speed percentiles (range: 1st percentile $r = 0.076$, $p = 0.230$ to 99th percentile $r = 0.399$, $p < 0.001$; 50th percentile $r = 0.132$, $p = 0.036$).

Conclusions: The 4-m gait speed is only weakly related to daily-life gait speed. Clinicians and researchers should consider that 4-m gait speed and daily-life gait speed represent two different constructs.

1. Introduction

Gait speed is regarded an important clinical measure because of its predictive ability of impending disability, morbidity and mortality [1,2] and is often referred to as the sixth vital sign [3]. To estimate a person's physical functioning and mobility, preferred gait speed is assessed in a standardized setting. However, standardized gait speed represents a person's functioning in ideal circumstances, depending on the applied assessment method [4], without cognitive dual tasking or surfaces demanding agility as encountered in daily life. The socially desirable

effect of participants trying to perform at their utmost best in presence of a professional might not be representative of their daily-life functioning. Being observed changes participants' behavior, also known as the Hawthorne effect [5]. Gait speed in a standardized setting likely reflects a person's maximum ability to carry out a task, whereas daily-life gait speed embodies a component of someone's physical activity behavior in daily life [6,7]. Physical activity is defined as "any bodily movement produced by skeletal muscles that requires energy expenditure" [8], of which ambulation is one of the main elements. Physical activity and physical performance have been shown to be

separate but associated domains of physical function [6,7].

Daily-life gait entails different circumstances of ambulation, depending on the location (indoor or outdoor walking), on the purpose (going to the supermarket, walking the dog, going up a flight of stairs, strolling or brisk walking), and on the use of assistive devices. Daily-life gait speed can be reliably obtained using inertial sensors that monitor physical activity over a recommended minimum duration of four days [9,10]. Research involving objective physical activity monitoring is a reasonably new area of interest and allows for quantifying both the amount and type of activities, as well as gait-related features such as cadence, step length and gait speed [7,11]. It has been shown that such features are associated with muscle function [12] and predict falls [7,13]. Two previous studies in small samples of community-dwelling older adults showed that cadence assessed in a standardized setting was considerably higher than the median cadence in daily life, and was more similar to the maximum and one-minute peak cadences in daily life [14,15]. These findings suggest that standardized assessments might be comparable to faster walking bouts in daily life, but this has to be confirmed in larger cohorts. The question remains whether standardized gait speed is representative of daily-life gait behavior or captures different constructs of physical function.

The aim of this study was to compare the 4-m gait speed of community-dwelling adults to the distribution of their daily-life gait speed; expressed as the peaks and the percentiles of daily-life gait speed. We hypothesized that the 4-m gait speed would correlate to the peak with higher daily-life gait speed, and to the higher percentiles of the distribution.

2. Methods

2.1. Study design

We analyzed data from a cross-sectional cohort that included 268 community-dwelling participants, recruited at the Grey Power debate events which took place in November 2014 at the VU University Medical Center, Amsterdam, the Netherlands [12]. The Grey Power debates were freely accessible lectures for the general population to promote healthy ageing and attracted a predominantly vital and motivated group of socially active community-dwelling participants. No exclusion criteria were applied. The research was reviewed and approved by the medical ethical committee of the VU University Medical Center. All participants signed written informed consent. Fourteen participants were excluded from the present analysis due to missing objective physical activity monitoring data from the inertial sensors, leaving data of 254 participants for analysis.

2.2. Data collection

2.2.1. Characteristics

Questionnaires were used to assess age, gender, polypharmacy, multimorbidity, current smoking, use of walking aid and falls in the preceding 12 months. Polypharmacy was defined as using five or more types of medications. Multimorbidity was defined as the presence of two or more chronic diseases including hypertension, myocardial infarction, stroke, chronic obstructive pulmonary disease, cancer, diabetes mellitus, osteoarthritis and Parkinson's disease. Body weight was assessed to the nearest 0.1 kg and height was assessed to the nearest 0.1 cm. Body mass index (BMI, in kg/m^2) was calculated from weight and height. Hand grip strength (HGS) was assessed to the nearest 1 kg using a handheld JAMAR dynamometer, expressed as the maximum score out of three attempts for each hand. Skeletal muscle mass index (SMI: skeletal muscle mass to the nearest 0.1 kg / $height^2$, in kg/m^2) was assessed using direct segmental multi-frequency bioelectrical impedance analysis (DSM-BIA; In-Body 230; Biospace Co., Ltd).

2.2.2. Four-meter gait speed

A timed 4-m walk test at preferred pace from a standing start was performed. The 4-m gait speed was assessed to the nearest 0.01 s using a stopwatch. Participants were instructed to walk at their comfortable speed. Walking distance exceeded the required four meters to prevent participants from slowing down before reaching the 4-m line. The fastest time of two trials was used for analyses and gait speed was expressed in m/s [4,16].

2.2.3. Daily-life gait speed

To assess the distribution of daily-life gait speed we used an inertial sensor with a tri-axial accelerometer (DynaPort MoveMonitor, McRoberts, The Hague, the Netherlands). The sensor was worn dorsally on the trunk at the level of L5 using an elastic belt for seven consecutive days. It was removed and reattached by the participant prior to and after water activities. The sensor was set to a sample frequency of 100 Hz, a range of ± 6 g and a resolution of 12 bit. The raw acceleration signal was classified in periods of non-wearing, locomotion, non-classified shuffling, sitting, standing and lying by the manufacturer's algorithms (McRoberts MoveMonitor, version 2.8.1). The accuracy of these algorithms have been validated in both younger and older community-dwelling adults [17,18]. The locomotion periods were divided into epochs of ten seconds. If the length of the locomotion period exceeded (multiples of) ten seconds, we analyzed the middle ten-second epochs. Prior to the estimation of the gait characteristics, the raw accelerations were multiplied by 9.81 to convert them from g into m/s^2. Subsequently, the raw accelerations were realigned with anatomical axes using the sensor's orientation with respect to gravity [19] and optimization of the left-right symmetry [20]. For each locomotion epoch, daily-life gait speed was estimated based on an inverted pendulum model as introduced by Zijlstra & Hof [9]. This method assumes a compass gait type with a circular trajectory of the sensor during each single support phase and determines step length by trigonometry from the peak-to-peak height differences obtained by double integration of the high-pass filtered vertical acceleration [step length = 2√((2 * leg length * amplitude of changes in vertical position) – (amplitude of changes in vertical position ^{2}))]. Leg length was estimated as 53% of body height [21]. MATLAB R2017b (MathWorks, Natick, USA) was used for the analyses and the determination of the gait characteristics.

2.3. Statistical analysis

2.3.1. Distribution of daily-life gait speed

Observation of the data suggested a non-Gaussian distribution of daily-life gait speed, following a bimodal distribution, which was also reported by others [7]. To assess the shape of the daily-life gait speed distribution per individual, we calculated the Ashman's D [7,22]. The Ashman's D enumerates the fit of a bimodal distribution to the observed values, and the higher the Ashman's D the better the fit. Ashman's D ≥ 2 is indicative of a bimodal distribution [22]. We first fitted a Gaussian mixture distribution with two components to each individual's data. Each component had a mean of μ and standard deviation of √(σ). To ensure a stable solution, we started with random initial values of μ, optimized the regularized fits, repeated this process 100 times and selected the fit with the largest log likelihood. We calculated Ashman's D as the difference between the μ divided by their pooled standard deviation √((Σσ)/2), which is essentially a z-test of the two distributions. Examples of the distributions of daily-life gait speed of eight participants were visualized using bar charts. The selection of the participants was based on their Ashman's D: two participants had a score < 2, two had a score between 2–3, two had a score between 3–4, and two had a score ≥ 4.

2.3.2. Corresponding percentile

Next, gait speed assessed during the 4-m walk test was compared to the distribution of daily-life gait speed, and the individual percentile

from the distribution that corresponded to the 4-m gait speed was calculated. For example, the corresponding percentile would be P50 if a participant performed the 4-m walk test at a speed that equaled the median value of the daily-life gait speed distribution. In case a participant walked faster during the 4-m walk test than ever during any of the daily-life epochs, the corresponding percentile was extrapolated as 100 plus the percentage increment from maximum daily-life speed, and would hence exceed P100.

2.3.3. Quantification of peaks and percentiles

To quantify the distribution of daily-life gait speed, we extracted the two peaks of the bimodal distribution of daily-life gait speed and the speeds at percentiles across the distribution. The 1st peak with the lowest daily-life gait speed presumably reflects smaller walking bouts indoors, and the 2nd peak with the highest gait speed presumably reflects walking during longer bouts outdoors [7]. Subsequently, we determined the 1st (P1), 5th (P5), 10th (P10), 25th (P25), 50th (P50), 75th (P75), 90th (P90), 95th (P95), 99th (P99) and 100th (P100) percentiles of the gait speed distribution of all ten-second gait epochs.

2.3.4. Pearson's correlations

Based on previous literature, 4-m gait speed assessed with a stopwatch was expected to be higher compared to daily-life gait speed assessed with inertial sensors [23]. In case of systematic differences between measuring gait speed with a stopwatch or an accelerometer, we wanted to investigate correlations between conditions taking into account such a potential offset between measurement methods. Therefore, Pearson's correlations were used to investigate the relationship between 4-m gait speed and the peaks and percentiles of daily-life gait speed. Correlations < 0.3 were considered negligible, 0.3–0.5 were considered low, 0.5–0.7 were considered moderate and ≥ 0.7 were considered high [24]. A Bland-Altman plot was used to visualize the comparison of 4-m gait speed with daily-life gait speed at the highest correlated percentile, to report the mean difference and investigate possible differences between slow and fast walkers.

2.3.5. Sensitivity analysis

As daily-life gait speed distributions rely on the gait classification method, we performed a sensitivity analysis of the Pearson's correlations. For this analysis, we used a more conservative selection of daily-life gait episodes of those with a main frequency > 0.2 Hz in vertical direction (method by Nait Aicha et al. [25]). Significance level was set at $\alpha = 0.05$. Statistical Package for the Social Sciences (IBM SPSS Statistics for Windows, Version 23.0. Armonk, NY, IBM Corp) was used for all analyses.

3. Results

The characteristics of the included participants are shown in Table 1. The median age was 66.7 years (IQR 59.4–72.5), and ranged from 20 to 91 years. A total of 167 participants (65.7%) were female. Two participants (0.8%) used a walking aid, and 41 (16.1%) had experienced a fall in the preceding year. The descriptives of 4-m and daily-life gait speed are shown in Table 2. The mean 4-m gait speed was 1.43 m/s (SD 0.21), and the mean P50 of daily-life gait speed was 0.90 m/s (SD 0.23).

The distributions of daily-life gait speed varied amongst the participants. Fig. 1 shows the distributions of daily-life gait speed of eight participants, with their bimodal fit indicating their two peaks. Only ten participants (4.0%) had an Ashman's D < 2, suggesting a unimodal rather than a bimodal distribution of their daily-life gait speed. The other 244 participants (96.0%) had an Ashman's D ≥ 2, indicating their daily life gait speed fitted a bimodal distribution. The mean 1st peak was 0.61 m/s (SD 0.15) and mean 2nd peak was 1.26 m/s (SD 0.23). Fig. 2 shows the distribution of all individuals' percentile of daily-life gait speed corresponding to their 4-m gait speed. The corresponding

Table 1
Participant characteristics.

Characteristics		N	Results
Age in years, median (IQR)		254	66.7 (59.4 – 72.5)
Female gender		254	167 (65.7)
Weight in kg, mean (SD)		253	73.3 (12.1)
Height in cm, mean (SD)		254	170.5 (9.0)
BMI in kg/m², mean (SD)		253	25.2 (3.8)
Polypharmacy[a]		253	14 (5.5)
Multimorbidity[b]		254	34 (13.4)
Use of walking aid		254	2 (0.8)
Falls in the previous 12 months		254	41 (16.1)
HGS in kg, mean (SD)	♂	87	44.6 (10.9)
	♀	167	30.3 (6.6)
SMI in kg/m², mean (SD)	♂	85	10.7 (1.0)
	♀	160	9.2 (0.9)

All variables are presented as N (%), unless otherwise indicated. BMI: Body mass index. HGS: Hand grip strength. IQR: Interquartile range. SD: Standard deviation. SMI: Skeletal muscle mass index.
[a]Number of medications > 4. [b]Number of morbidities > 1.

Table 2
Descriptives and Pearson's correlations of 4-m gait speed and daily-life gait speed expressed as peaks and percentiles.

	Gait speed (m/s), mean (SD)	Bivariate correlation, r (p-value)
4-m gait speed	1.43 (0.21)	
Daily-life gait speed		
1st peak	0.61 (0.15)	0.005 (0.936)
2nd peak	1.26 (0.23)	0.181 (0.004)
P1	0.27 (0.05)	0.076 (0.230)
P5	0.34 (0.06)	0.095 (0.131)
P10	0.41 (0.08)	0.079 (0.209)
P25	0.60 (0.14)	0.036 (0.565)
P50	0.90 (0.23)	0.132 (0.036)
P75	1.22 (0.23)	0.224 (< 0.001)
P90	1.41 (0.20)	0.315 (< 0.001)
P95	1.49 (0.19)	0.352 (< 0.001)
P99	1.59 (0.18)	0.399 (< 0.001)
P100	1.71 (0.19)	0.386 (< 0.001)

SD: Standard deviation. P: Percentile.

percentiles ranged from P30.0 to P138.2, with a median value of P91.2 (IQR P75.4 – P98.6). In seven participants (2.8%), the 4-m gait speed corresponded to a percentile equal to or below the median of daily-life speed. A total of 26 participants (10.2%) walked faster during the 4-m walk test than they ever did during the seven days of monitoring in daily-life.

Table 2 shows a low correlation of 4-m gait speed with the peaks of daily-life gait speed (1st peak r = 0.005, p = 0.936; 2nd peak r = 0.181, p = 0.004). The correlations of 4-m gait speed with percentiles of daily-life gait speed are also shown in Table 2. These correlations were negligible to low, yet increased with higher percentiles. The lowest correlation was found for P1 (r = 0.076, p = 0.230), and the highest correlation was found for P99 (r = 0.399, p < 0.001). The median (P50) showed a negligible correlation with the 4-m gait speed (r = 0.132, p = 0.036). The Bland-Altman plot comparing 4-m gait speed with P99 gait speed is shown in Fig. 3. The mean difference between 4-m and P99 gait speed was 0.16 m/s (SD 0.22), and there was no systematic effect of slow or fast walking. The sensitivity analysis using a more conservative selection of daily-life gait episodes omitted a median 6.4% of ten-second epochs (IQR 4.5–10.1), and resulted in minor adjustments in the results of the Pearson's correlations (Supplementary Table 1).
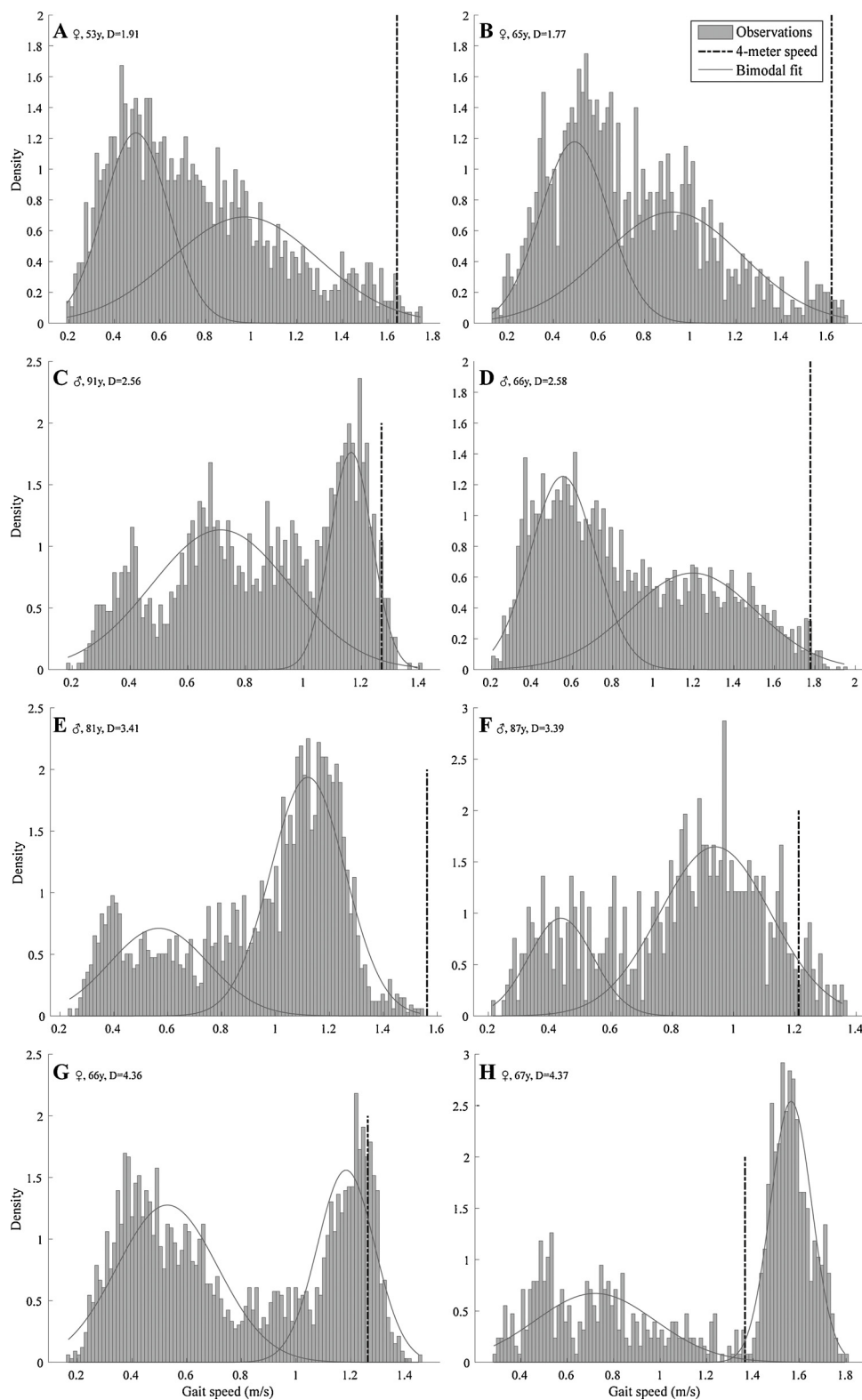
Fig. 1. Examples of individual distributions of daily-life gait speed in eight participants. Grey bars represent the observations of daily-life gait speed expressed as the density over all ten-second gait epochs for each individual; the solid grey line represents the optimal bimodal fit; the vertical dotted black line represents the 4-m gait speed. D: Ashman's D.

4. Discussion

We compared 4-m gait speed at preferred pace to the distribution of daily-life gait speed. As expected, the gait speed that the participants adopted during the 4-m walk test corresponded to the high ends of, or

even exceeded, the gait speeds that they adopted in daily life. The 4-m gait speed was poorly related to the peaks and percentiles of daily-life gait speed distribution.

The negligible to low correlations between 4-m gait speed and daily-life gait speed indicate that standardized gait speed is not
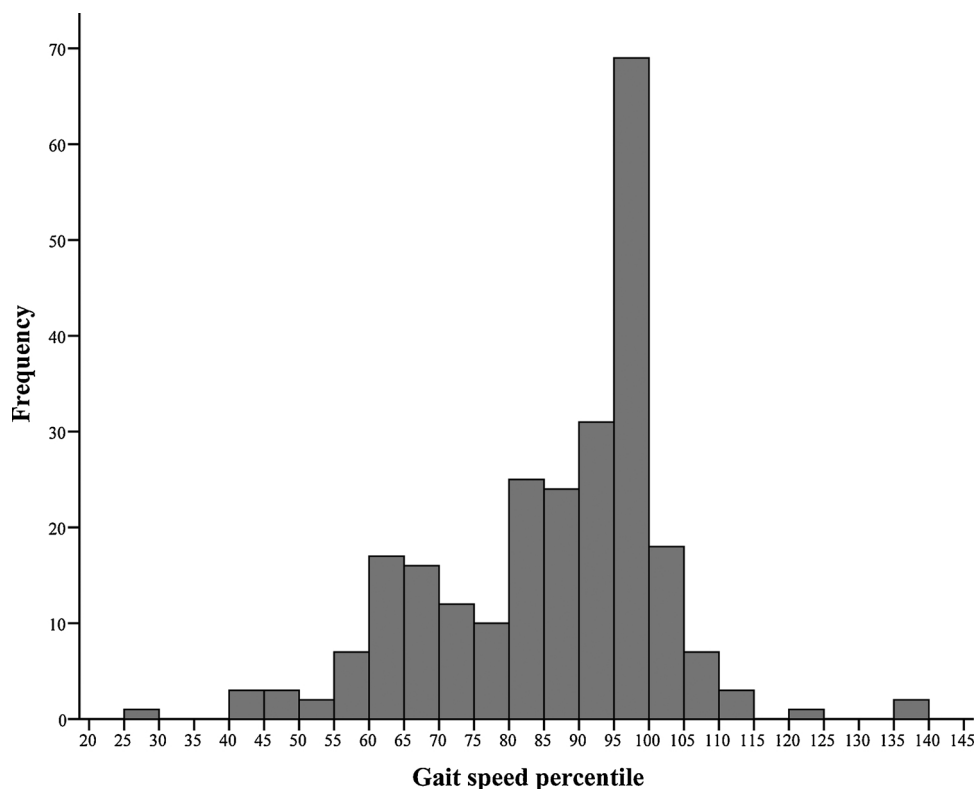
Fig. 2. Distribution of all individuals' percentile of the daily-life gait speed corresponding to their 4-m gait speed (N = 254). A percentile exceeding P100 reflects an extrapolated percentile due to a 4-m gait speed faster than ever during any of the daily-life epochs.

representative of what people do in the real world. This underpins the notion that 4-m gait speed, reflecting physical performance, and daily-life gait speed, reflecting physical activity, are two separate domains of physical function [6]. Previous literature is in line with our findings,

showing negligible to low correlations when comparing different measures of physical performance versus physical activity in a small cohort of older adults from retirement communities [26], and in small cohorts of community-dwelling older adults [27,28]. Opposed to our
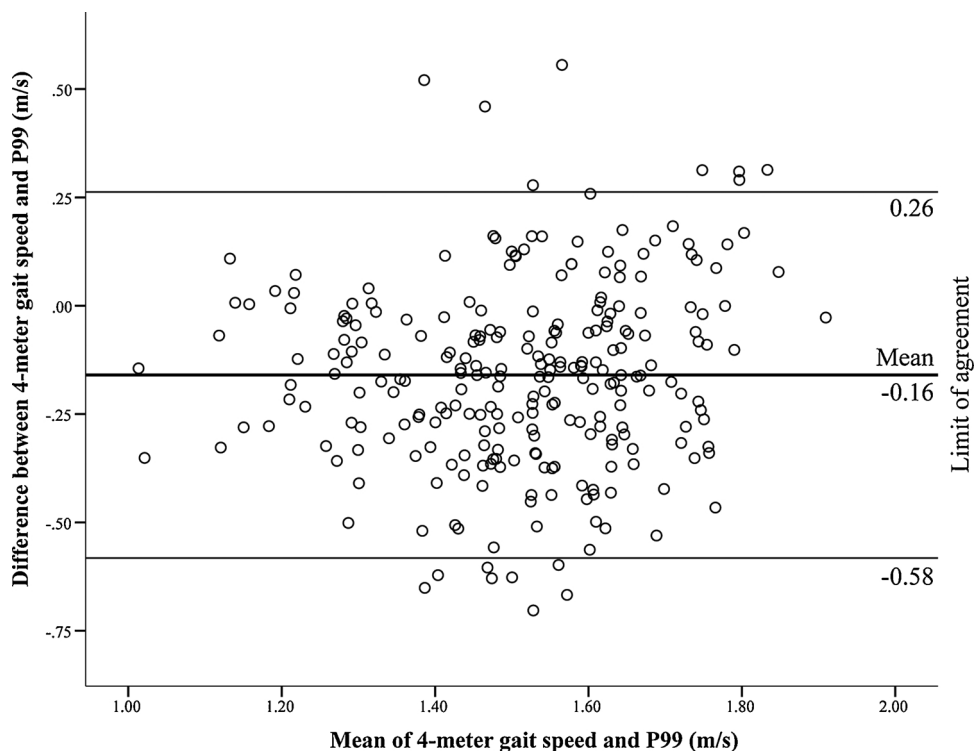

Fig. 3. Bland and Altman plot for comparison of 4-m gait speed and the 99th percentile of the daily-life gait speed distribution. Representation of the limits of agreement, from -1.96 * Standard Deviation to +1.96 * Standard Deviation.

findings, a previous study in 51 community-dwelling older adults showed a moderate correlation of standardized walking cadence with median daily-life walking cadence (r = 0.69) [14]. This study included older adults only (age range 76–96 years). In a study by Pitta and colleagues, physical performance measures showed moderate correlations with physical activity measures in 50 chronic obstructive pulmonary disease patients, but low correlations in 25 healthy participants with a mean age of 66 years (SD 5) [29]. This suggests that correlations between standardized and daily-life gait speed may be higher for older and chronically ill individuals, because they may perform more often closer to their maximum capacity during daily-life functioning. Our sample of relatively healthy and fit community-dwelling participants limited us in exploring this further, however, this sample with an age range of 20 to 91 year old participants already showed some multimorbidity and functional decline.

The included population showed heterogeneous distributions of daily-life gait speed, and most participants showed a bimodal distribution, with one of the peaks at a higher gait speed, presumably reflecting the preferred gait speed during longer episodes of walking outdoors. Brodie and colleagues showed that a bimodal distribution of cadence, as opposed to a unimodal distribution, was associated with a lower risk of falls in 96 community-dwelling older adults [7]. The Ashman's D is an attractive method to objectively locate two peaks in the distribution of daily-life gait speed, however, caution should be taken in the interpretation of the results, because the number of peaks was lower in 4% of the population and might have exceeded two in a small proportion of individuals.

Assessment of daily-life gait speed and its distribution is challenging. Daily use of the monitor provides challenges because participants could detach them during specific periods of time, in addition to displacing it from the lower back or inverted, all of which can be detected by the monitor. Daily-life locomotion includes turning, stepping, uneven surfaces, wearing shoes with high heels and so on, all providing a slightly different acceleration signal, that also differs between participants. Previous studies have estimated gait speed in daily life using innovative indoor measurement systems, with monitoring systems mounted inside the homes of participants for continues monitoring of gait speed [30,31]. In spite of these promising measurement systems, these assessments are limited to indoor walking and do not represent the full distribution of gait speed in daily-life. Outdoor activity has been shown to be vital for fully capturing the physical activity pattern and was positively associated with functioning, being socially active and experiencing depressive symptoms [32,33]. Estimating daily-life gait speed using inertial sensors has its limitations, because it is only an approximation of the actual value, in our study based on an inverted pendulum model, leg length and the vertical acceleration signal [9]. Although this method to estimate gait speed has been shown highly accurate (with a mean difference between actual and predicted speed of $\pm$ 0.05 m/s), the maximum observed difference in gait speed on an individual level can be as high as 20% [9]. In addition, there is no consensus on the selection criteria of gait episodes. We applied a sensitivity analysis using a method described by Nait Aicha and colleagues [25] that uses a more conservative selection of daily-life gait episodes and omits episodes that may reflect shuffling or other activities, which are debatably classified as locomotion. The results of the sensitivity analyses were comparable to the primary findings.

Different methodology for the assessment of 4-m and daily-life gait speed can be considered a limitation of this study. The 4-m walk test at preferred pace was assessed using a stopwatch from a standing start, including the acceleration phase. Although this might have led to a slight underestimation of the preferred gait speed [4], we nevertheless observed corresponding values at the higher ends of the daily-life gait speed distribution. During the 4-m walk test we did not collect any acceleration signals, limiting the comparison between 4-m and daily-life gait speed calculations. A previous study showed a small underestimation of gait speed collected with inertial sensors when compared

to treadmill walking [23], implying a slight underestimation of daily-life gait speed, which may counterbalance the underestimation of the 4-m walk test. Furthermore, walking distances covered during daily-life gait episodes were variable and included epochs with acceleration, deceleration or different levels of steady state gait; this limited us in comparing and adjusting speed for the different walking distances and potential acceleration or deceleration.

Assessing daily-life gait speed in addition to standardized assessments could be of value for clinicians and researchers, because of its representation of daily life gait behavior in the context of environmental influences and various activities of daily living. Application of daily-life gait speed assessments could inform about declines in speed over long periods of time, and may be used in formal care through remote monitoring or self-management using smart systems [34]. For standardized gait speed assessments, clinically meaningful changes have been reported in older adults [35]. How to report meaningful changes and reliability of the distribution of daily-life gait speed needs to be investigated in future research.

In conclusion, we compared standardized gait speed to the distribution of daily-life gait speed in community-dwelling adults. The 4-m gait speed corresponded to a percentile that was in the high range of speeds in daily life, and was not correlated to the peaks and percentiles of daily-life gait speed. Daily-life gait speed captures different information of physical function than 4-m gait speed. Clinicians and researchers should take into account that 4-m gait speed and daily-life gait speed represent two different constructs of physical function.

Contributors

Jeanine M. Van Ancum was responsible for conceptualization, methodology, formal analysis, and drafting, reviewing and editing the manuscript.

Kimberley S. van Schooten was responsible for conceptualization, data curation, methodology, software, formal analysis, and drafting, reviewing and editing the manuscript.

Nini H. Jonkman was responsible for conceptualization and supervision, and reviewing and editing the manuscript.

Bas Huijben was responsible for data curation, methodology, software, and reviewing and editing the manuscript.

Rob C. van Lummel was responsible for data curation, methodology, software, and reviewing and editing the manuscript.

Carel G. M. Meskers was responsible for reviewing and editing the manuscript, and supervision.

Andrea B. Maier was responsible for conceptualization, funding acquisition, reviewing and editing the manuscript, and supervision.

Mirjam Pijnappels was responsible for conceptualization, funding acquisition, reviewing and editing the manuscript, and supervision.

Conflict of interest

The authors declare that they have no conflict of interest.

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Ethical approval

The research was reviewed and approved by the medical ethical committee of the VU University Medical Center. All participants gave written informed consent. The privacy rights of human subjects was always observed.

Provenance and peer review

This article has undergone peer review.

Research data (data sharing and collaboration)

There are no linked research data sets for this paper. The data sets generated are not publicly available, but are available from the principal investigator on reasonable request.

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Appendix A. Supplementary data

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