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Validation of a smartphone embedded inertial measurement unit for measuring postural stability in older adults

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ABSTRACT

Background: Identifying older adults with increased fall risk due to poor postural control on a large scale is only possible through omnipresent and low cost measuring devices such as the inertial measurement units (IMU) embedded in smartphones. However, the correlation between smartphone measures of postural stability and state-of-the-art force plate measures has never been assessed in a large sample allowing us to take into account age as a covariate.

Research question: How reliably can postural stability be measured with a smartphone embedded IMU in comparison to a force plate?

Methods: We assessed balance in 97 adults aged 50–90 years in four different conditions (eyes open, eyes closed, semi-tandem and dual-task) in the anterio-posterior and medio-lateral directions. We used six different parameters (root mean square and average absolute value of COP displacement, velocity and acceleration) for the force plate and two different parameters (root mean square and average absolute value of COM acceleration) for the smartphone.

Results: Test-retest reliability was smaller for the smartphone than for the force plate (intra class correlation) but both devices could equally well detect differences between conditions (similar Cohen's d). Parameters from the smartphone and the force plate, with age regressed out, were moderately correlated (robust correlation coefficients of around 0.5).

Significance: This study comprehensively documents test-retest reliability and effect sizes for stability measures obtained with a force plate and smartphone as well as correlations between force plate and smartphone measures based on a large sample of older adults. Our large sample size allowed us to reliably determine the strength of the correlations between force plate and smartphone measures. The most important practical implication of our results is that more repetitions or longer trials are required when using a smartphone instead of a force plate to assess balance.

1. Introduction

Falls are the leading cause of injuries in older adults [1]. Between 28 and 35 % of people aged over 65 fall at least once every year [2], causing about 25,000 deaths annually in the US alone [1]. In addition, about 20 % of falls lead to serious injuries with 10 % of falls requiring admission to the hospital [3], resulting in substantial economic costs ($31.3 billion in the US in 2015) [1]. Both intrinsic (e.g., strength, vision,…) and extrinsic (e.g., medications, footwear, environment,…) factors contribute to fall risk in older adults [4]. An important intrinsic factor is poor postural control [5]. Good postural control requires sufficiently accurate signals from the sensory systems, effective cognitive processing and a well-functioning musculoskeletal system [6]. It is crucial to be able to identify people with poor postural control because they have a higher risk of falling. This can only be achieved on a large scale based on low-cost validated devices to measure postural stability outside the laboratory. The omnipresence of smartphones with embedded inertial measurement units (IMUs) and the quickly increasing adoption of smartphones by older adults provide such opportunity [7].

A force plate is the state-of-the-art device to measure postural stability [8] and provides the motion of the center of pressure (COP) over time. Force plate derived measurements of the COP (e.g. increased

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velocity, displacement, sway area, variability and root mean square displacement) have been linked to balance control and fall-risk in older adults [9,10]. However, while some portable force plates have been developed and validated (e.g [11]), the use of force plates outside the laboratory remains marginal.

In contrast, the widespread use of smartphones and health applications for mobile devices could provide broad access to objective balance assessment through the smartphone's embedded IMU. The concurrent validity of several devices with embedded IMU for measuring postural stability has been tested [12]. Several studies have compared postural stability measures between force plates and IMUs from smartphones [13,14] (systematically reviewed in [12,15]). While most studies found significant relationships between smartphone and force plate outcomes, these were often very variable from one condition to another. Furthermore, the small sample sizes used in previous studies prevented assessing the strength of these relationships reliably [16] as underpowered studies tend to overestimate the size of the correlations [17]. Furthermore, several of the previous studies [12,15] did not take age as a covariate, which tends to artificially increase the correlation coefficients.

Therefore, our aim was to estimate the strength of the relationship between smartphone embedded IMU and force plate measures of postural stability in a large group (~100) of older adults across four conditions (eyes open, eyes closed, dual-task and semi tandem condition).

2. Methods

2.1. Participants

99 adults between 50 and 90 years old participated in this study. Two participants were excluded from the analysis due to respectively inability to complete the cognitive task and an acute loss of lower limb sensitivity and strength leaving us with 97 participants (42 males and 55 females). Participants were recruited through local advertisements at gathering places for older adults, through mailings to organizations for older adults, and within the social network of the research team. Exclusion criteria were: 1) severe neurological, medical, or psychiatric diseases; 2) problems with understanding test instructions as assessed by the examiner based on their interaction with the subject; 3) mobility aids other than a walking stick. The study was approved by the local ethics committee of UZ/KU Leuven (S61583). All participants signed an informed consent form in accordance with the Declaration of Helsinki.

2.2. Materials

COP movement was measured by a BTrackS Balance Plate (BBP, BTrackS™ Balance Plate, California, USA) at a sample frequency of 25 Hz [11]. The BBP contains force transducers beneath each corner of the rectangular plate (40 cm × 60 cm). The BtrackS Explore Balance software was used for analysing the data.

Linear and rotational accelerations of a Samsung Galaxy S7 smartphone (Samsung, Seoul, Korea) attached to the subject's waist near the body's center of mass (COM) (Fig. 1) were measured by the embedded IMU using a custom-made application at a mean sample frequency of 500 Hz (range 499 Hz–509 Hz).

2.3. Procedure

We used a cross-sectional study design to examine the concurrent validity of the Samsung Galaxy S7 smartphone in static balance conditions. Measurements were performed at the Faculty of Movement and Rehabilitation Sciences or at the participant's home. The force plate was always placed on a flat and firm surface. First, the participant filled out a fall risk assessment (Fig. 2). Next, the participant was instructed to stand barefoot on the force plate in a comfortable posture, hands positioned at

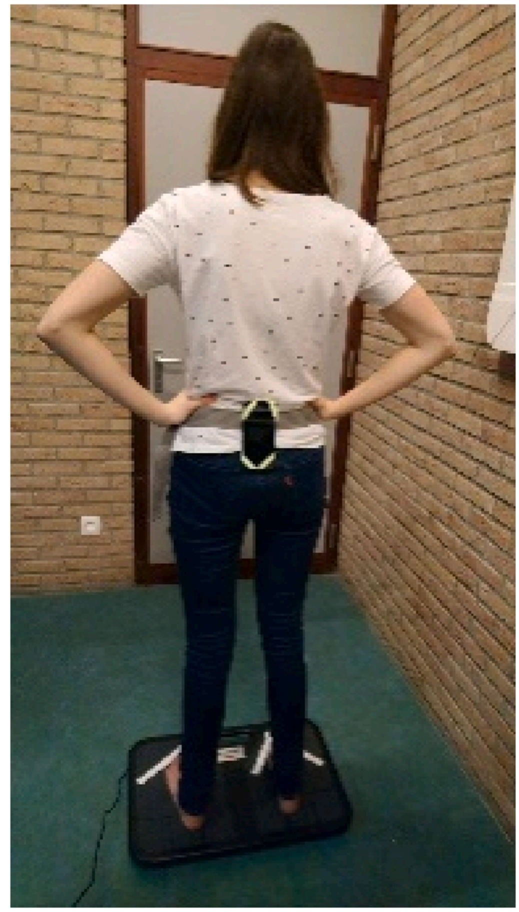

Fig. 1. Test setup. Participants stood barefoot on the force plate (1 m in front of the wall) in a comfortable posture, both hands positioned at hip level. The smartphone was attached to the participant's back at the level of the second sacral vertebra, near the body center of mass.

hip level. The feet's position was tape-marked to maintain the same position across conditions. The instructor positioned the belt with the smartphone on the participant's back at the level of the second sacral vertebra, near the body COM, using the posterior superior iliac spine as a reference (Fig. 1). Care was taken that the belt was sufficiently tight to limit relative movements with respect to the body. During the entire test procedure, the instructor stood behind the participant to guarantee their safety. Balance was assessed in four conditions: 1) bipodal stance with eyes open (BSEO), 2) bipodal stance with eyes closed (BSEC), 3) a dual-task consisting of bipodal stance with eyes open and a cognitive task (CTEO), and 4) semi-tandem stance with eyes open (STEO). During the dual task, participants were asked to count down aloud in steps of 7 from a random number between 100 and 120. Each balance test lasted 35 s and was repeated four times. The first trial from each condition was considered a familiarisation trial and was not included in our analysis. Participants were instructed to stand as still as possible while looking at a standardised fixation point on the wall, 1 m in front of them. Between conditions, participants got off the force plate and had the opportunity to rest while the instructor changed the set-up. For the fourth balance test, the instructor turned the force plate 90° to allow participants to place both feet on the plate in semi-tandem stance. If the participant lost their balance during the trial, the trial was repeated.

2.4. Data analysis

Only data collected during the last 30 s of each 35 s trial was analyzed. COP position measurements from the force plate were

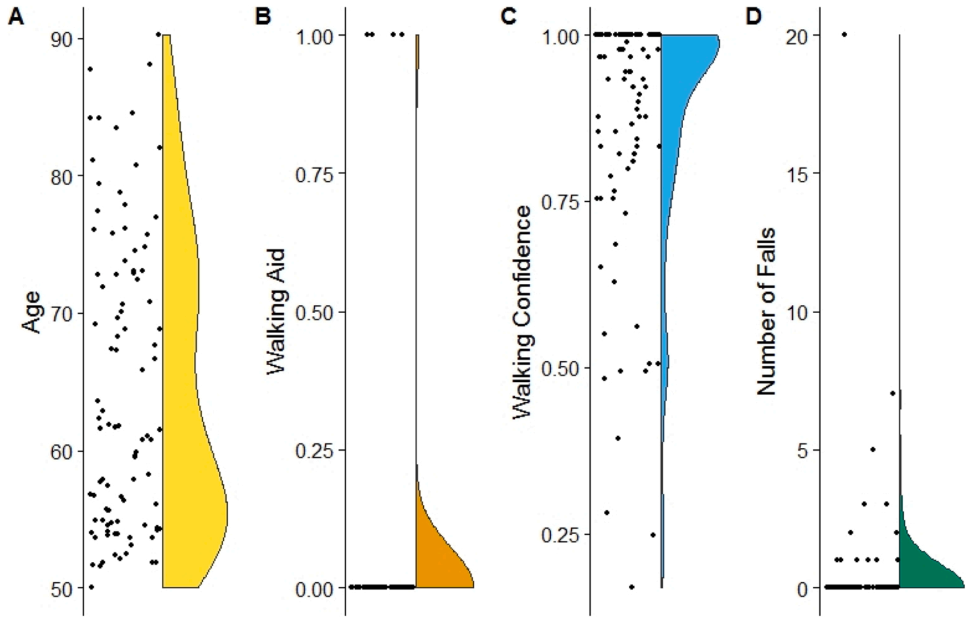

Fig. 2. Description of participants (individual points + smoothed distribution): A) age of the participants; B) using a walking-aid (yes = 1, no = 0); C) walking confidence as measured by a visual scale (high = 1, low = 0); D) self-reported number of falls in the last year.

processed with a Savitzky-Goley filter (5th polynomial order and frame length of 7) to obtain filtered position, velocity and acceleration signals. The average value was subtracted from each position, velocity and acceleration signal. This gave us three signals in two different directions (anterior-posterior and medio-lateral). For each of these signals, we computed the root-mean-square (RMS) and the mean absolute value (Mean) resulting in 12 force plate outcome measures (2 directions x 3 derivatives x 2 analysis types). We only used smartphone acceleration data in the anterior-posterior and medio-lateral directions (smartphone-based reference). We first subtracted the mean from the signal and then computed a weighted RMS and mean absolute value as the sampling frequency was variable, resulting in four smartphone outcome measures. Data processing was done in Matlab (R2018b, Mathworks, Natick, Massachusetts, USA). Raw data and analysis scripts can be accessed at https://osf.io/vpd79/?view_only=07b131728d934f5e9948fb545a7810e2.

The above mentioned parameters were selected based on a study with a similar experimental set-up for measuring the concurrent validity of a mobile device according to a force plate to measure postural stability and fall risk in elderly [13].

2.5. Statistical analysis

Statistical analyses were performed in R [18] based on the average outcome measures over the three trials, except when analyzing intra-class correlations. We used a robust correlation method (80 % winsorized correlation) using the wincor function from the WRS2 package [19].

First, we correlated all parameters with age. The confidence interval of these coefficients was computed via a bootstrap procedure. Second, we considered the eye opens condition as reference and computed the magnitude of the difference for the three other conditions by means of Cohen's d (within-subject difference between the two conditions divided by its standard deviation). Confidence intervals were obtained by the ci.sm function from the MBESS package [20]. Third, we computed the intra-class correlation coefficient across the three trials for each participant with the test-retest function (trt) from the Relfeas package [21].

Because all parameters were correlated with age, we regressed age out of all ensuing correlation analyses. Fourth, we computed the winsorized correlation between all parameters from the force plate and all parameters from the smartphone. We did not correct for multiple comparisons, as we were not interested in the significance of these correlations but in their magnitude. The confidence interval of these coefficients was computed via a bootstrap procedure. Finally, we performed a factor analysis on all signals (partialling out the effect of age) from the force plate and the smartphone separately considering postural stability as the only latent factor. We used the fa function from the psych package [22] with oblimin rotation. The factors were obtained by maximum likelihood factoring method and the factor scores by the regression method. Factor scores for the force plate and smartphone obtained separately were then correlated with a winsorized correlation. Scripts for statistical analysis can be accessed at https://osf.io/vpd79/?view_only=07b131728d934f5e9948fb545a7810e2.

3. Results

3.1. Demographics

To investigate whether a smartphone IMU was sufficiently reliable to assess balance, we collected data in 97 adults between 50 and 90 years old with a force plate and a smartphone fixed on the bottom of their back during four balance tasks. Few participants used a walking aid, some participants did not have maximal walking confidence, and 13 participants had already experienced falls (Fig. 2, data derived from fall risk assessment).

3.2. Effect of age on balance

All outcome parameters were correlated with age with correlation coefficients around 0.5 for force plate parameters derived from COP velocities and accelerations while these correlations were around 0.35 for the smartphone parameters, showing that the force-plate might be slightly more sensitive to measure age-related changes in postural-sway than the smartphone (Fig. 3A). In other words, while one needs 30 participants to detect an effect of age with the force plate, one needs 61 participants with the smartphone (80 % power, significance level of 0.05).

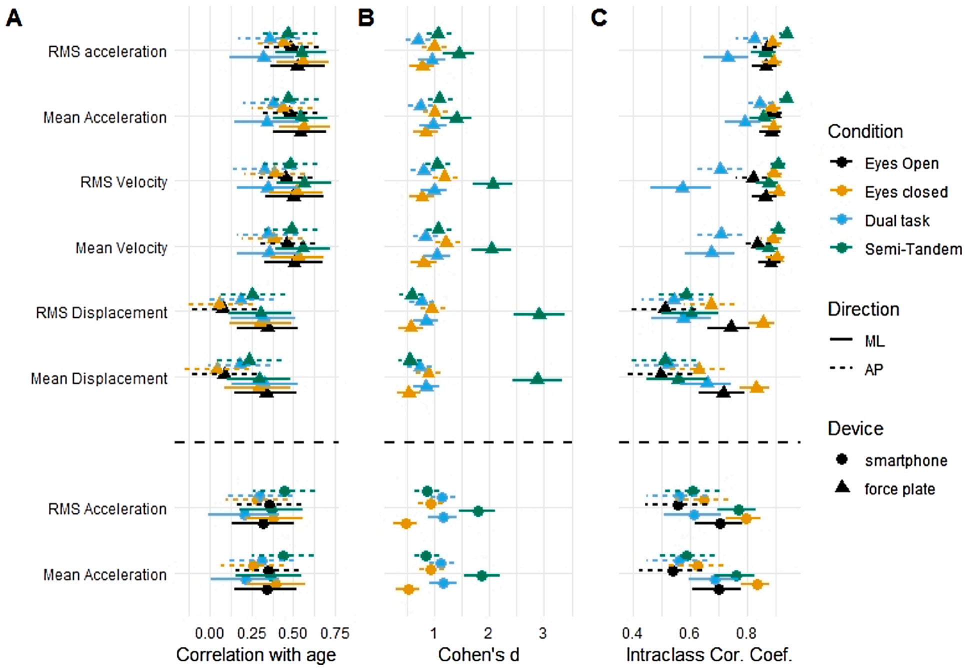

Fig. 3. A) Sensitivity of the different measurement to age-related changes in balance (symbol and error bar represent mean and confidence interval of the winsorized correlation coefficient) for the different directions (medio-lateral: ML and anterio-posterior: AP), conditions, and devices. B) Sensitivity of the different measurements to the difference in postural sway in the different experimental conditions relative to the eyes open condition (symbol and error bar represents mean Cohen's d and confidence interval). C) Reliability of the different measurements over the three test trials as assessed by the intra-class correlation coefficient (ICC) (symbol and error bar represent mean ICC and confidence interval). All variables were first corrected for age. The data represented here can be assessed in table format (along with the original data and data processing scripts) on https://osf.io/8w9ea/?view_only=07b131728d934f5e9948fb545a7810e2 (TableAge.xlsx).

3.3. *Sensitivity of outcome parameters to different conditions*

Force plate and smartphone derived outcome parameters captured differences between the different conditions and the eyes open condition (taken as reference) equally well with effect sizes around 1 (Fig. 3B). Effect sizes were largest for the semi-tandem condition in the medio-lateral direction but varied a lot among the different force plate outcome parameters.

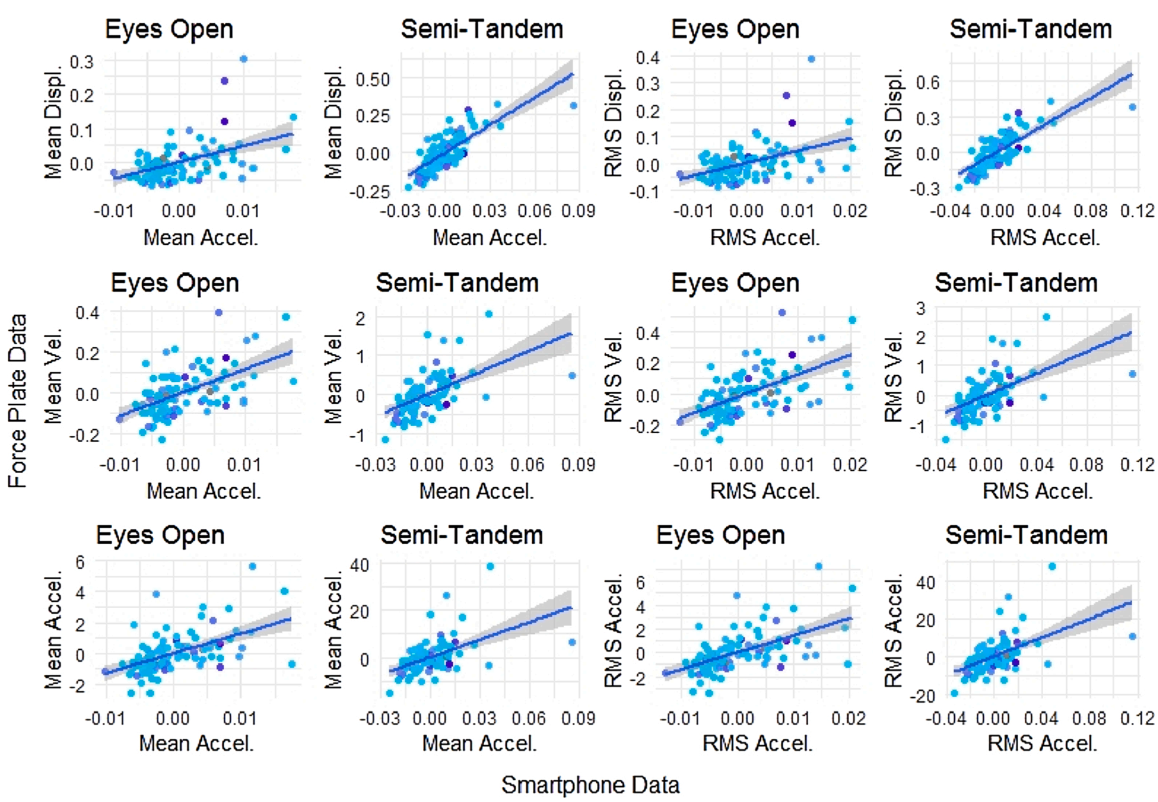

Fig. 4. Correlation between outcome parameters for the smartphone (horizontal axis) and for the force plate (vertical axis) for the eyes open (EO) and semi-tandem (ST) conditions. Outcome parameters for the force plate vary along the rows (displacement - Disp, velocity - Vel and acceleration - Acc). First two columns focus on the mean absolute value, last two on the root-mean-square value. The color code represents walking confidence with high walking confidence in light blue and low walking confidence in dark blue. Blue line represents the regression line for the normal regression with the grey area representing its 95 % confidence interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

3.4. Reliability of outcome parameters

The test-retest reliability of the outcome parameters across the three repetitions differed between conditions (Fig. 3C). In the dual-task condition, measures derived from COP position and velocity were more variable than in the other conditions, reflecting that the cognitive load imposed by dual-tasking can be highly variable from trial to trial. When not considering the dual-task condition, the test-retest reliability of the smartphone outcome parameters was moderate (0.5–0.75) to good (0.75–0.9) while the test-retest reliability of the force plate outcome parameters was excellent (>0.9).

3.5. Correlation between smartphone and force plate outcomes

It is crucial to know whether someone with bad postural stability would be characterized as such with both devices. Therefore, we correlated the outcome parameters of the smartphone with those of the force plates.

We used robust correlation methods to avoid spuriously high correlations due to a few points being away from the main population as illustrated in Fig. 4 for the eyes open and semi-tandem conditions in the medio-lateral direction. Walking confidence was not highly linked to high postural sway as darker points are scattered along both axes and not on the top right of the graphs (Fig. 4).

Force plate and smartphone outcome parameters are correlated but the extent of these winsorized correlation accounting for age depends on condition and direction with a range from 0.14 to 0.82 (Fig. 5). Furthermore, correlations are often larger in more challenging conditions (medio-lateral direction in semi-tandem, anterior-posterior direction during eyes closed) than in the easier conditions.

To assess how smartphone and force plate measures of postural sway are related, we used factor analysis on the force-plate and smartphone data (partialling out the effect of age) separately in order to extract the latent factor linked to the control of balance with both devices. Factor analysis is a variance decomposition technique that looks for a shared source of variance (latent factor) across all postural stability outcomes from all conditions for both devices separately. Hence, the factor score is a single condition-independent postural stability outcome across conditions for each participant and each device. The factor scores obtained from either all force plate or all smartphone measures were correlated with a winsorized correlation coefficient of 0.58 (CI=[0.42, 0.75], Fig. 6).

4. Discussion

We investigated the extent to which the IMU embedded in a smartphone could be a valid instrument for measuring postural stability in older adults. While previous studies suggested a link between measures of postural stability obtained by a force plate and IMU, none of them was able to assess the magnitude of this relationship with sufficient accuracy because of small samples and the presence of covariates such as age.

We gained new insights in the measurement of postural stability with an IMU as compared to with a force plate. First, both IMUs and force plates could detect correlations between postural stability parameters and age but the force plate measures derived from COP position and velocity were slightly more sensitive. Second and in line with previous studies [23,24], differences across conditions could be detected equally well with both systems. Third, the test-retest reliability was larger for the force plate than for the smartphone but was also dependent on sway direction and condition with the dual-task condition being the least reliable. Finally, the robust correlation coefficient between the parameters from the smartphone and the force plate (with age regressed out) was very variable across conditions and parameters but was mostly moderate (around 0.4–0.5). The factor analysis, which takes all conditions, directions and parameters into account, was moderately correlated as well (r = 0.58, CI=[0.42, 0.75]).

While these results support previous conclusions that smartphone embedded IMUs could be used to assess postural instability [13], our results also highlight that they are not as good as force plates. IMUs have several advantages including their small size and price. However, they are not as precise and are more variable from trial-to-trial as force plates. Therefore, smartphones may not fully replace force plates in the future.

Future studies using IMUs to measure postural stability should use longer trials because this could potentially increase the reliability of the measures. Yet, one also needs to pay attention to fatigue effects when trials are becoming longer.

The location of the smartphone on the body should be investigated further. In Hsieh et al. [13], participants held the smartphone vertically against their chest while we attached it to the subject's lower back, which should be close to the body COM, therefore yielding easier to interpret measures. However, spine movements during sway might have limited the accuracy of the smartphone measures.

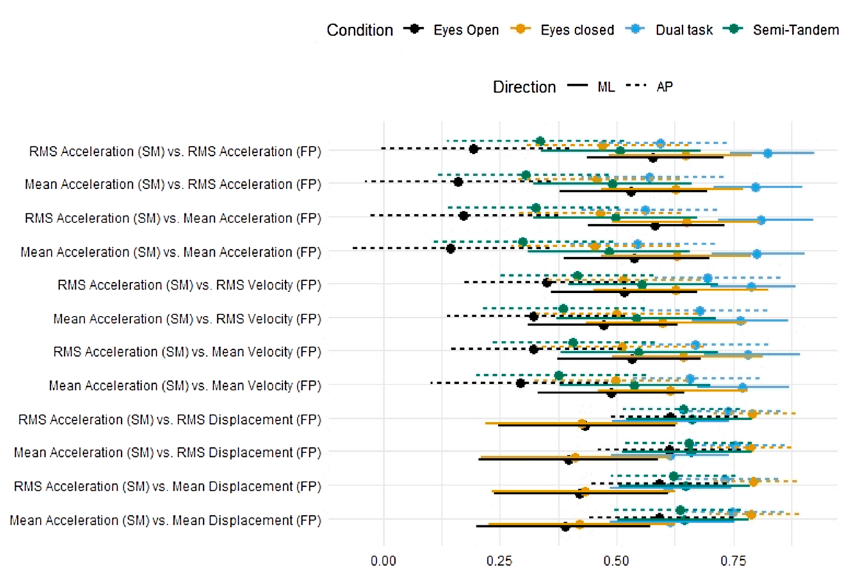

Fig. 5. Correlation between force plate and smartphone parameters. Mean and bootstrapped confidence intervals for all correlations between every pair of outcome parameters from the force plate (FP) and smartphone (SM) in all directions and all conditions. Correlation coefficients were obtained via winsorized correlations accounting for the effect of age.

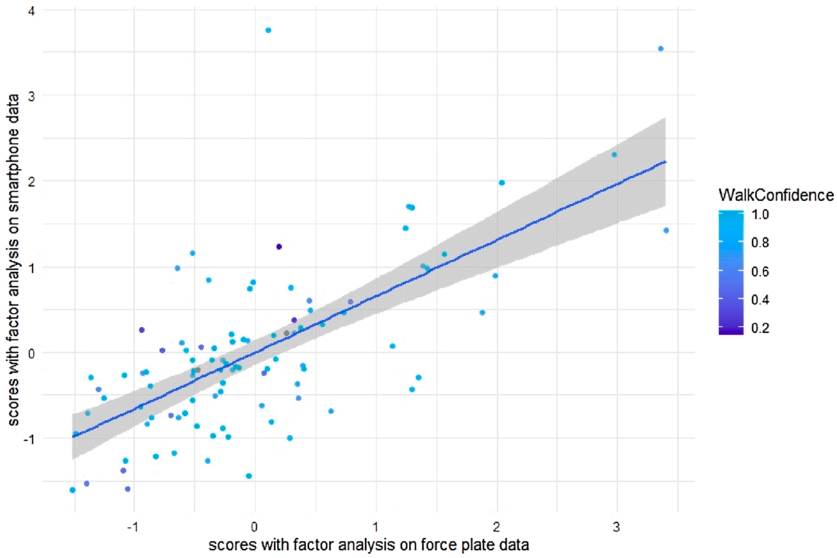

Fig. 6. Correlation between factor score obtained from force plate outcomes and factor score obtained from the smartphone outcomes accounting for the effect of age. Color of the points provides info on the walking confidence of the different participants. Blue line represents the regression line for the normal regression with the grey area representing its 95 % confidence interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

The reported correlations could be underestimated as the smartphone and the force plate measure different signals. While the force plate measures COP location, the smartphone provides accelerations of a point close to the body's COM. COP and COM positions are related through the body dynamics but this relation is not linear [5]. Moreover, different subjects may use different correcting strategies with different movements in the ankle, knee and hip joints depending on e.g. age and fear of falling, which is expected to negatively affect the correlation between both measures [25].

The semi-tandem condition is the best choice for smartphone-based assessment of balance due to its relatively high ICC (Fig. 3) combined with a moderate correlation with the force-plate measures (Fig. 5) across both directions. With the smartphone, test-retest reliability was higher in the eyes closed and semi-tandem conditions in the ML direction and the correlation with the force plate outcomes was highest in the ML and AP direction in the semi-tandem condition (Fig. 5). Furthermore, correlations between COP displacement and COM acceleration were most consistent across directions in the semi-tandem condition. In contrast to a previous study, which reported that force plate measures of bipodal stance in the AP are most sensitive to age-related changes in postural stability [26], our results show that the outcomes are equally sensitive to age across several conditions (Fig.3).

Our study bears several limitations. First, smartphone placement was not always optimal due to body curvature, and hence the measurement axis of the IMU was not always perfectly aligned with the anterio-posterior direction. Integration of gyroscope data from the smartphone embedded IMU might be used to correct this aberrant position in the data analysis. Different test environments (people's home and the Faculty of Movement and Rehabilitation Sciences) and ambient noise may have influenced the results. Third, our population consisted only of healthy older individuals. Therefore, the applicability of our results to other populations (e.g., younger people and individuals with balance disorders) should be investigated. Fourth, we did not use a clinical scale, e.g. Berg's Balance Scale, to assess our participants. Future studies should investigate whether clinical screening could be complemented by quantitative assessment with IMUs to detect older adults with a higher fall risk. Fifth, results might depend on IMU properties. We selected a smartphone that allowed us to collect high frequency (500 Hz) acceleration data but spectral density analysis of the acceleration signals revealed that a sample frequency of 200 Hz is sufficient.

In conclusion, a smartphone embedded IMU could be used to assess balance in older adults but trials need to be longer or repeated more often as compared to force plate measurements in order to deal with the lower test-retest reliability. The use of smartphone embedded IMUs will facilitate the assessment of balance under a wider range of conditions, such as standing on uneven surfaces and over longer time periods, and might thereby improve ecological validity of balance assessment.

Declaration of Competing Interest

There are no conflicts of interest.

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