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Smartphone technology can measure postural stability and discriminate fall risk in older adults

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ABSTRACT

Background: Falls are the leading cause of injury related death in older adults. Impaired postural stability is a predictor of falls but is seldom objectively assessed in clinical or home settings. Embedded accelerometers within smartphones offer potential to objectively measure postural stability. The purpose of this study was to determine if a smartphone embedded accelerometer can measure static postural stability and distinguish older adults at high levels of fall risk.

Methods: Thirty older adults (age: 65.9 ± 8.8) underwent seven balance tests while standing on a force plate and holding a smartphone against their chest in a standardized order. Participants also completed the Physiological Profile Assessment to assess their fall risk. Center of pressure (COP) parameters from the force plate including velocity in the anterioposterior (AP) and mediolateral (ML) directions and 95% confidence ellipse were derived. Maximum acceleration and root mean square (RMS) in ML, AP and vertical axes were derived from the smartphone. Spearman rank-order correlations between force plate and smartphone measures were conducted, and receiver operating characteristic (ROC) and the area under the curves (AUC) were constructed to distinguish between low and high fall risk.

Results: There were moderate to strong significant correlations between measures derived from the force plate and measures derived from the smartphone during challenging balance conditions (ρ = 0.42–0.81; p < 0.01–0.05). The AUC for ROC plots were significant for all COP measures during challenging balance conditions (p < 0.01–0.05). The AUC for ROC plots were significant for RMS vertical and AP during challenging balance conditions (p = 0.01–0.04).

Significance: This study provides evidence that a smartphone is a valid measure of postural stability and capable of distinguishing fall risk stratification in older adults. There is potential for smartphones to offer objective, fall risk assessments for older adults.

1. Introduction

Falls are the leading cause of injury related death in older adults 65 years and older [1]. Falls not only lead to physical injuries, but they also lead to activity curtailment, physiological deconditioning, and reduction in quality of life [1]. The number of annual fall-related injuries in the United States is expected to be 5.7 million by 2030 [2]. In 2015, the estimated medical cost of falls was 50 billion dollars [3]. Given the frequency and severity of falls, there is a need to identify factors that predict and prevent falls.

One consistent predictor of falls is impaired postural stability [4]. Previous studies have suggested that postural instability (e.g., balance impairment), evaluated with center of pressure (COP) movement as the gold standard balance measure, is highly related to the risk of falling [5,6]. Balance impairment quantified with motion capture cameras and stand-alone accelerometers have also shown to relate to fall risk [7]. Despite this established link between balance impairment and falls, objective measurement of postural stability is rarely performed in clinical settings due to expensive equipment and required expertise [8]. More commonly, clinical measures of balance such as the functional reach task, single leg stance, or timed up and go are prevalent in the clinic as these tests involve little instrumentation or specialized equipment [9]. Unfortunately, these tests have low discriminative power and may not be sensitive enough to assess small changes in balance associated with age-related impairment [10,11].

Mobile technology, such as smartphones, offers potential to provide

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objective measures of balance assessment. Smartphones are embedded with accelerometers that may be used to measure balance. As of 2017, 59% of adults 65–69 years old, 49% of adults 70–74 years old, and 31% of adults 75–79 years old own a smartphone [12]. Given the high ownership of smartphones in older adults, along with its cost-efficiency and portability, smartphones have significant potential to provide a tool for balance screening in non-laboratory settings.

Body-worn accelerometers also provide potential for balance and gait assessment. A systematic review analyzed the use of inertial sensors for fall risk assessment in older adults [13]. While body-worn accelerometers provide potential for accurate and objective fall risk assessment, almost all inertial sensors in the investigation required assistance from personnel to operate, analyze, and interpret the data. Smartphones may overcome this limitation by leveraging the public's familiarity with smartphone technology and embedded accelerometer to objectively measure balance. Objective balance assessment that involves minimal assistance and is simple to use may improve technology acceptance and usage among older adults [14].

A recent review on mobile technology to assess balance and fall risk reported that, while smartphone technology is becoming a promising tool to assess posture, few studies have validated smartphones with gold standard techniques [15]. This review indicates a need for further studies to compare balance measures with mobile technology to gold standard technology in older adults. Additionally, while one study in the review found differences in balance between frail and non-frail older adults as measured with a tablet [16], it is unclear if balance measurements from mobile technology are sensitive to differences in fall risk.

To address these limitations, this investigation sought to determine if a smartphone can measure postural stability during progressive, static balance tasks compared to posturography collected with a force plate in older adults. The second aim was to determine if a smartphone can discriminate between older adults at low and high risk of falling compared to posturography. Based on previous studies examining accelerometry, we hypothesized that the smartphone would be comparable to a force plate in measuring static balance, and that the smartphone will discriminate between older adults at a low and high risk of falling.

2. Methods

2.1. Participants

Thirty healthy, older adults participated in this investigation. Participants were excluded from the study if they scored more than two standard deviations from the established norms (i.e. total score < 20) on the Modified Telephone Interview for Cognitive Status (TICS-M) [17], were non-ambulatory, had vision impairments, or cannot read 14 point font. All procedures were approved by the University of Illinois at Urbana-Champaign Institutional Review Board, and all participants completed written informed consent prior to participation.

2.2. Protocol & data analysis

All participants underwent static balance assessments while standing on a force plate (Bertec Inc, Columbus, OH) and holding a smartphone (Samsung Galaxy S6, Samsung, Seoul, South Korea) with their dominate hand medially against the chest along the sternum (Fig. 1). Researchers ensured that participants held the phone to the proper orientation aligned to the anteroposterior (AP), mediolateral (ML), and vertical axes for each trial. Prior to each participant the force plate was calibrated and configured to obtain an accurate measure of COP. The force plate was sampled at 1000 Hz and the accelerometer from the smartphone was sampled at an average of 200 Hz. Seven static balance tests were conducted in the following order for 30 s each: 1) eyes open, 2) eyes open with concurrent cognitive challenge (dual task), 3) eyes closed, 4) eyes closed with dual task, 5) semi tandem stance, 6) tandem stance, and 7) single leg stance. Two trials of each static balance task were performed. If participants lost their balance during the 30 s, the trial was discarded, and they were given an opportunity to repeat the trial. These balance tasks were chosen to challenge base of support and sensorimotor systems, and have distinguished between older adult fallers and non-fallers [18]. During the dual-task, participants simultaneously subtracted by seven from a random number between 100 and 200. This serial sevens subtraction test has been used as a cognitive challenge in various populations including older adults [19].

Fig. 1. Experimental set-up. Participant holds a smartphone vertically against his chest while standing on a force plate.

COP data from the force plate for each trial was exported and processed with a 4th order, low pass Butterworth filter at a cutoff frequency of 10 Hz using a custom MATLAB script (Mathworks Inc., Natick, MA). Parameters included in the analysis were 95% confidence ellipse and velocity in the anteroposterior (AP) direction and mediolateral (ML) direction. These parameters were chosen because they are predictive of falls and recurrent falls in older adults [18]. From the smartphone, maximum acceleration in the ML, vertical, and AP directions and root mean square (RMS) in the ML, vertical, and AP axis were exported and processed. These measures were chosen they have been

previously validated against motion capture cameras and differentiated between frail and non-frail older adults [16,20,21].

2.3. Statistical analysis

Statistical analyses were performed using IBM Statistical Package for the Social Sciences (SPSS) for Windows, version 22 (IBM Corp, Armonk, NY). Force plate and smartphone measures were averaged for the two trials for each condition. Missing data, which indicated inability to complete a balance task, was filled using the maximum value of the variable from the sample [22]. All missing data points were filled using the maximum value. Five participants were unable to complete the tandem stance, and ten participants were unable to complete the single leg stance.

Validity between measures derived from the force plate and measures derived from the smartphone was assessed with Spearman rank-order correlations for all balance conditions. Correlations coefficients of 0.1 were considered small, 0.3 were considered moderate, and 0.5 were considered large [23]. Receiving operating characteristic (ROC) curves were constructed and the area under the curve (AUC) was calculated to determine the level of discrimination between older adults with low and high risk of falling using all force plate measures and RMS from the smartphone measures. Statistical significance was set at $\alpha = 0.05$.

To analyze the ability of smartphone measures to distinguish individuals with high fall risk, participants completed the physiological profile assessment (PPA) [24]. The PPA test measures fall risk based on vision, reaction time, leg strength, proprioception, and balance. Per guidelines, a PPA score above one was considered high risk, and below one was considered low risk [24].

3. Results

Demographic information of all participants is presented in Table 1. Thirty older adults participated, and 22 were classified as low fall risk while eight were classified as high fall risk. On average, low fall risk older adults scored 0.2 on the PPA while high fall risk older adults scored 2.4 on the PPA.

From the force plate, COP velocity AP ranged from 9.996 mm/s to 47.951 mm/s and COP velocity ML ranged from 3.967 mm/s to 52.823 mm/s. COP area ellipse ranged from 177.277 mm^2 to 14,448.789 mm^2. From the smartphone, maximum acceleration ML ranged from 0.627 to 5.105 m/s^2, maximum acceleration vertical ranged from 10.175 to 12.466 m/s^2, and maximum acceleration AP ranged from 1.830 to 13.800 m/s^2. RMS ML ranged from 0.077 m/s^2 to 0.870 m/s^2, RMS vertical ranged from 9.811 m/s^2–10.115 m/s^2, and RMS AP ranged from 0.194 m/s^2 to 0.536 m/s^2. These values are similar to previously reported values of static postural stability of healthy, older adults [20,25–28]. All measures derived from the force plate and smartphone for all conditions are included in the supplementary material.

Spearman correlations found weak to moderate correlations between force plate COP measures and smartphone measures as shown in Table 2. Correlations were higher between COP velocity and area ellipse with RMS in the vertical and AP directions. During semi-tandem, tandem, and single leg conditions, all force plate measures were significantly correlated with RMS ML, vertical, and AP from the smartphone ($\rho = 0.463$–0.812; $p < 0.001$–0.05).

ROC curves were constructed for COP velocity AP and ML and 95% confidence ellipse (Fig. 2) and RMS AP, ML, and Vertical (Fig. 3) to discriminate between older adults at low and high risk for falls. The AUC for ROC curves are indicated in Table 3. The AUC for COP velocity ML ranged from 0.731 to 0.783, AUC for COP velocity AP ranged from 0.655 to 0.840, and AUC for 95% confidence ellipse ranged from 0.693 to 8.848. For COP velocity ML, the AUC was statistically significant during eyes open ($p = 0.009$), eyes open dual task ($p = 0.005$), eyes closed dual task ($p = 0.019$), tandem ($p = 0.024$), and single leg ($p = 0.045$) conditions. For COP velocity AP, the AUC was significant during eyes open ($p = 0.009$), eyes open dual task ($p = 0.040$), eyes closed dual task ($p = 0.005$), and eyes closed dual task ($p = 0.040$) conditions. For 95% confidence ellipse, the AUC was significant for all conditions except eyes open condition ($p = 0.004$-0.05).

The AUC for RMS ML ranged from 0.467-0.734, RMS vertical from 0.582-0.755, and RMS AP from 0.603-0.837. The AUC for RMS ML was nearing significance for tandem stance ($p = 0.052$). The AUC for RMS vertical was statistically significant during semi tandem ($p = 0.024$)

Table 1
Demographic information of participants in the study. Values are mean ± standard deviation.

	Older Adult Low Risk Falls	Older Adult High Risk Falls
Age (years)	64.8 ± 4.5	72.3 ± 6.6
Gender	14 females; 8 males	4 females; 4 males
Physiological Profile Assessment Score	0.2 ± 0.6	2.4 ± 0.5

Table 2
Spearman Correlations between force plate measures and smartphone measures during all balance conditions. *Denotes significance of $p \leq 0.05$. **Denotes significance of $p \leq 0.01$. COP = center of pressure; RMS = root mean square; AP = anteroposterior; ML = mediolateral.

		Force Plate Measures		
Condition	Smartphone Measures	COP Velocity AP	COP Velocity ML	95% Confidence Ellipse
Eyes Open	Max ML	0.446*	0.220	0.047
	Max Vertical	0.362	0.151	0.399*
	Max AP	0.049	−0.105	−.090
	RMS ML	0.253	0.202	0.152
	RMS Vertical	0.430*	0.241	0.255
	RMS AP	0.417*	0.072	0.190
Eyes Closed	Max ML	0.478**	0.444*	0.268
	Max Vertical	0.428*	0.276	0.431*
	Max AP	0.035	0.131	0.032
	RMS ML	0.436*	0.348	0.253
	RMS Vertical	0.507**	0.208	0.330
	RMS AP	0.522**	0.566**	0.413*
Eyes Open Dual Task	Max ML	0.298	0.375*	0.058
	Max Vertical	0.215	0.196	0.121
	Max AP	−0.240	−0.188	−0.217
	RMS ML	0.457*	0.429*	0.275
	RMS Vertical	0.484**	0.423*	0.348
	RMS AP	0.533**	0.483**	0.348
Eyes Closed Dual Task	Max ML	0.090	0.301	0.073
	Max Vertical	0.131	0.270	0.230
	Max AP	0.127	0.275	0.172
	RMS ML	0.189	0.270	0.074
	RMS Vertical	0.204	0.319	0.324
	RMS AP	0.443*	0.505**	0.391*
Semi-Tandem	Max ML	0.463*	0.520**	0.376
	Max Vertical	0.490**	0.508**	0.607**
	Max AP	0.124	0.196	0.016
	RMS ML	0.466*	0.558**	0.598**
	RMS Vertical	0.393*	0.498**	0.657**
	RMS AP	0.127	0.373*	0.706**
Tandem	Max ML	0.659**	0.422*	0.537**
	Max Vertical	0.698**	0.474*	0.427*
	Max AP	0.203	−0.117	−0.141
	RMS ML	0.641**	0.503*	0.573**
	RMS Vertical	0.732**	0.589**	0.670**
	RMS AP	0.623**	0.491*	0.800**
Single Leg	Max ML	0.543*	0.540*	0.617**
	Max Vertical	0.740**	0.678**	0.720**
	Max AP	0.436	0.501*	−0.114
	RMS ML	0.565**	0.525*	0.696**
	RMS Vertical	0.812**	0.670**	0.586**
	RMS AP	0.495*	0.512*	0.538*

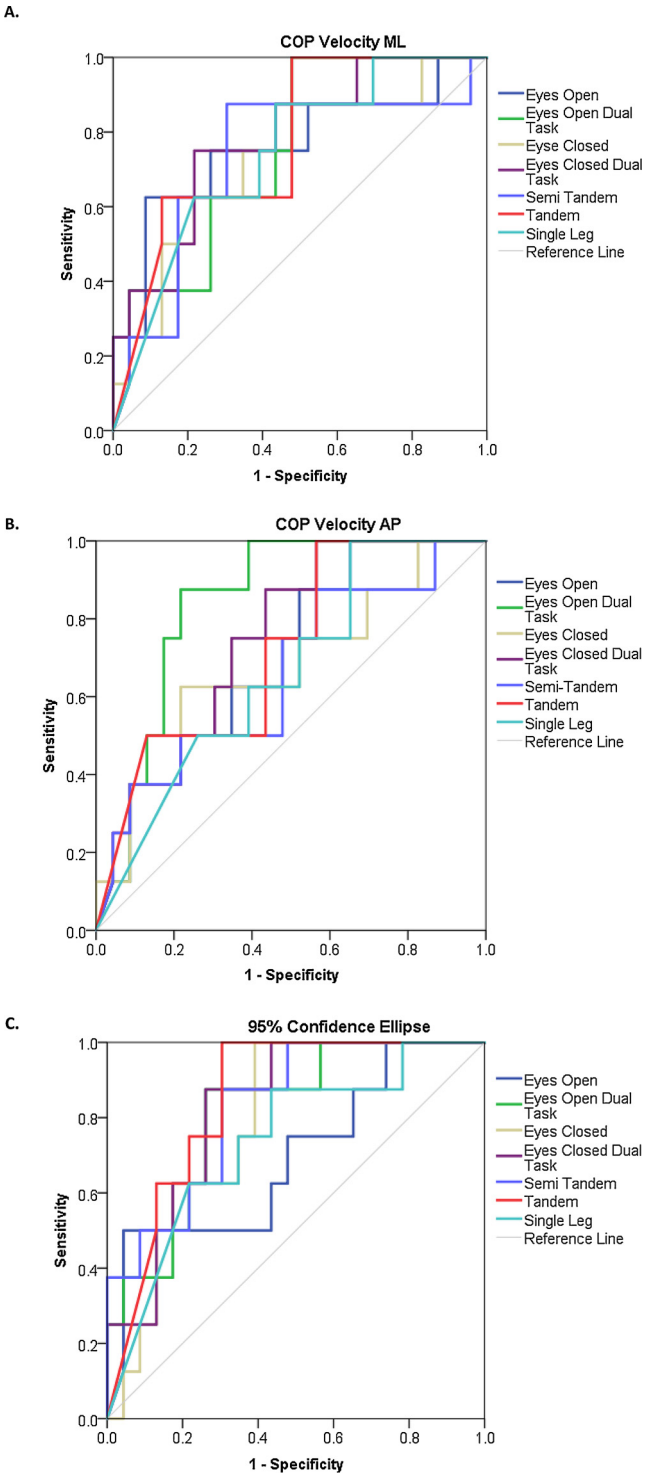

Fig. 2. Receiving Operating Curves for center of pressure (COP) velocity in the mediolateral direction (A) and anteroposterior direction (B) and 95% confidence ellipse (C) derived from the force plate for all participants during seven static balance tasks.

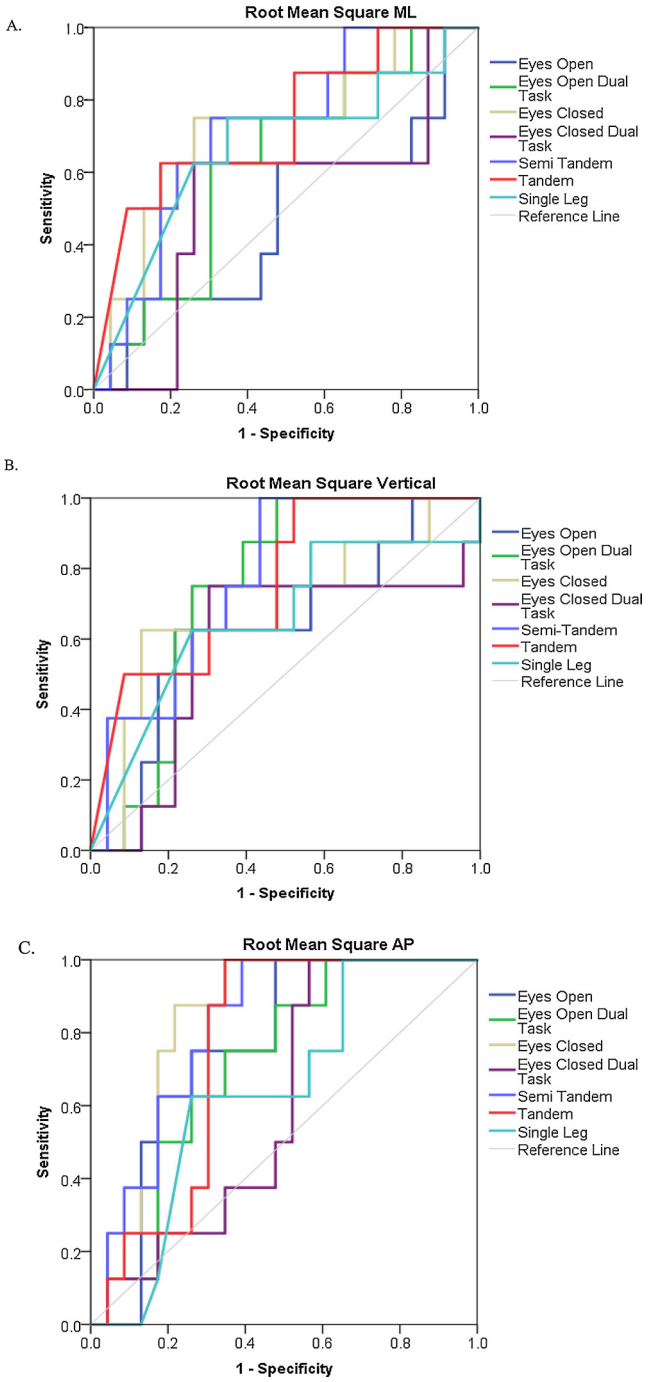

Fig. 3. Receiving operating curves for root mean square in the mediolateral (ML) (A), vertical (B), and anteroposterior (AP) (C) directions derived from the smartphone for all participants during seven static balance conditions.

and tandem ($p = 0.034$). For RMS AP, AUC was statistically significant during eyes open ($p = 0.030$), eyes closed ($p = 0.005$), semi-tandem ($p = 0.009$), and tandem ($p = 0.034$).

4. Discussion

The purpose of this investigation was to determine the validity of smart-phone based postural assessment in older adults. The results from this study support our hypothesis that a smartphone is a valid measure of postural stability in older adults. There were significant correlations between COP velocity AP, COP velocity ML, and 95% confidence area ellipse to RMS AP, RMS ML, and RMS vertical during challenging balance conditions. In addition, from the ROC curves, the smartphone was comparable to the force plate in discriminating between older adults at low and high risk of falling during semi-tandem and tandem conditions. RMS in the AP and vertical directions from the smartphone appear to be comparable to COP velocity and area ellipse from the force plate in discriminating fall risk in older adults.

Our results support previous studies that have also measured

Table 3
Area under the curve (AUC) of receiving operating characteristics plots of force plate and smartphone measures during static balance conditions. Force plate measures included center of pressure (COP) velocity anteroposterior (AP) and mediolateral (ML), and smartphone measures included root mean square (RMS) AP, vertical, and ML. *Denotes significance of $p \leq 0.05$.

Condition	COP Velocity ML		COP Velocity AP		95% Confidence Ellipse		RMS ML		RMS Vertical		RMS AP	
	AUC	*p*-value	AUC	*p* -value	AUC	*p* - value	AUC	*p* -value	AUC	*p* -value	AUC	*p* -value
Eyes Open	0.761	0.030*	0.698	0.009*	0.693	0.109	0.467	0.786	0.630	0.279	0.761	0.030*
Eyes Open Dual Task	0.747	0.040*	0.840	0.005*	0.810	0.010*	0.625	0.299	0.745	0.042*	0.717	0.071
Eyes Closed	0.734	0.052	0.668	0.162	0.788	0.017*	0.717	0.071	0.685	0.125	0.837	0.005*
Eyes Closed Dual Task	0.783	0.019*	0.747	0.040*	0.826	0.007*	0.527	0.821	0.582	0.498	0.603	0.391
Semi Tandem	0.731	0.055	0.655	0.198	0.826	0.007*	0.717	0.071	0.772	0.024*	0.815	0.009*
Tandem	0.772	0.024*	0.717	0.071	0.848	0.004*	0.734	0.052	0.755	0.034*	0.755	0.034*
Single Leg	0.742	0.045*	0.658	0.190	0.736	0.050*	0.668	0.162	0.658	0.190	0.644	0.232

postural stability with mobile technology. Past studies found that RMS derived from a smartphone is comparable to standalone accelerometers or motion capture cameras [20,21,27]. This aligns with current results which observe that RMS derived from the smartphone to be most comparable to COP velocity and area ellipse. RMS from a smartphone appears to be the most comparable to gold-standard devices. Max acceleration was also comparable to COP measures during semi-tandem, tandem, and single leg stance, similar to a previous study that used acceleration derived from a tablet to measure static balance [21]. Our correlations were also found to be strong ($\rho > 0.5$) between RMS from the smartphone to COP Velocity and 95% Confidence Ellipse from the force plate. These strong and significant correlations suggest high validity between the two devices. Our findings suggest that max and RMS acceleration derived from a smartphone is well comparable to COP velocity and area from a force plate.

Our results are also in line with previous studies that have used body-worn accelerometers located at the trunk to measure acceleration during gait and balance tasks. For instance, Doi et al. [29] found that the harmonic ratio of accelerometers worn on the lower and upper trunk significantly discriminated between older adult fallers and non-fallers. The AUC reported for discrimination was similar to AUC from RMS AP derived from the smartphone. Furthermore, another study using a triaxial accelerometer worn at the trunk in individuals with multiple sclerosis found strong correlations in RMS acceleration between the accelerometer and a force plate during eyes open, eyes closed, and eyes open foam balance conditions [30]. Our strong correlations between RMS acceleration derived from the smartphone and COP velocity derived from the force plate suggest similar findings. However, the inertial sensors used in both studies require operator assistance. While research assistants were present for safety, older adults potentially could use the smartphone to measure balance independently. Further research is needed to determine if older adults can confidently and safety use smartphone technology to assess static balance.

This study is the first to determine that a smartphone can discriminate between older adults at low and high risk of falling. Specifically, RMS in the AP and vertical directions appears to distinguish between levels of fall risk during semi-tandem and tandem stance. While there are no pre-determined categories of low, moderate, and strong AUC values, an AUC of above 0.7 has shown to be a strong discriminator in behavioral science studies [31]. Furthermore, previous studies validating accelerometers to distinguish fall risk in older adults have reported AUC values between 0.65-0.85, suggesting that the accelerometer embedded smartphone has high validity in discriminating between low and high fall risk older adults [13]. Therefore, not only are smartphones comparable to force plates in measuring balance, but measuring balance using a smartphone may also be useful in identifying older adults at a low or high risk of falling. RMS derived from a smartphone is able to capture age-related neuromuscular changes associated with aging that are related to elevated fall risk. It is important to note that RMS was not as sensitive in discrimination as was COP velocity or area, but this is expected as force plates are the gold standard balance measure and can capture minute changes in postural sway [32]. Smartphones, however, are more widely available and cost-efficient than force plates, and our results demonstrate that they can be used to measure static balance and distinguish fall risk in older adults.

Smartphone technology may provide a solution to increase balance and fall risk screening among older adults. While force plates are highly sensitive in capturing balance, they are expensive and require trained expertise [33]. On the other hand, clinical tests are subjective and lack sensitivity [10,11]. This study demonstrates that smartphones are valid in measuring static balance and can discriminate between fall risk. While smartphones should not replace force plates in measuring static balance, they may provide an alternate tool to evaluate balance when force plates are unavailable. Additionally, providing smartphone accelerometry for postural measurement is intended for the lay public rather than skilled researchers. Providing access to objective, balance assessment for the public may increase awareness of balance and falls and identify those in need of treatment.

Because balance and falls screening is seldom conducted in clinical settings, smartphones may provide quick, objective measurement in the clinic. In addition, with the high and growing ownership of smartphones among older adults [12], smartphones may also provide objective balance measurement in non-clinical settings. Identifying older adults with poor balance is a necessary first step to provide an intervention to ultimately reduce their risk of falling.

While this study successfully tested postural control using mobile technology, there are some limitations. This study determined validity of the smartphone and discrimination between fall risk, but we did not test usability of the smartphone. If the smartphone is not usable for older adults, then there may be less willingness to use mobile technology to measure balance [34]. We also did not assess reliability of the smartphone in this context. Future steps should determine the reliability and usability of smartphone technology in measuring postural stability and fall risk in non-clinical settings. Additionally, while researchers checked the orientation of the smartphone during each balance task, it is possible that the smartphone was not held in perfect alignment to the axes for every trial. However, smartphone technology aims to provide balance assessment in home or clinical settings, and this approach is more ecologically valid as older adults are unlikely to hold a smartphone in perfect alignment without extra assistance.

In conclusion, the purpose of this study was to determine if a smartphone device can measure postural stability, and if a smartphone can discriminate between older adults at low and high risk of falling. Our results suggest that RMS derived from a smartphone is comparable to COP velocity and area derived from a force plate. In addition, RMS AP and vertical discriminated between older adults with low and high fall risk and was comparable to discrimination from force plate measures. Smartphone technology can measure static postural stability and has potential to improve balance screening among older adults.

Declaration of interest

JJS has partial ownership in Sosnoff Technologies, LLC a company that may be affected by the research reported in the enclosed paper. This conflict of interest is managed by plan approved by the University of Illinois at Urbana-Champaign.

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