Gait & Posture 69 (2019) 85–90

Contents lists available at ScienceDirect

Gait & Posture

journal homepage: www.elsevier.com/locate/gaitpost

Full length article

Assessment of gait kinetics in post-menopausal women using tri-axial ankle accelerometers during barefoot walking

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ARTICLE INFO

Keywords:
Ground reaction force
Accelerometer
Post-menopausal
Modeling

ABSTRACT

Background: Physical activity (PA) interventions, designed to increase exposure to ground reaction force (GRF) loading, are a common target for reducing fracture risk in post-menopausal women with low bone mineral density (BMD). Unfortunately, accurate tracking of PA in free-living environments and the ability to translate this activity into evaluations of bone health is currently limited.

Research question: This study evaluates the effectiveness of ankle-worn accelerometers to estimate the vertical GRFs responsible for bone and joint loading in post-menopausal women at a range of self-selected walking speeds during barefoot walking.

Methods: Seventy women, at least one year post-menopause, wore Actigraph GT3X + on both ankles and completed walking trials at self-selected speeds (a minimum of five each at fast, normal and slow walking) along a 30 m instrumented walkway with force plates and photocells to measure loading and estimate gait velocity. Repeated measures correlation analysis and step-wise mixed-effects modelling were performed to evaluate significant predictors of peak vertical GRFs normalized to body weight (pVGRFbw), including peak vertical ankle accelerations (pVacc), walking velocity (Vel_w) and age.

Results: A strong repeated measures correlation of r = 0.75 (95%CI [0.71-0.76] via 1000 bootstrap passes) between pVacc and pVGRFbw was observed. Five-fold cross-validation of mixed-model predictions yielded an average mean-absolute-error (MAE[95%CI]) and root-mean-square-error (RMSE) rate of 5.98%[5.61–6.42] and 0.076 [0.069-0.082] with a more complex model (including $Vel_{w,}$) and 6.80%[6.37–7.54] and 0.087BW[0.081-0.095] with a simpler model (including only pVacc), when comparing accelerometer-based estimations of pVGRFbw to force plate measures of pVGRFbw. Age was not found to be significant.

Significance: This study is the first to show a strong relationship among ankle accelerometry data and high fidelity lower-limb loading approximations in post-menopausal women. The results provide the first steps necessary for estimation of real-world limb and joint loading supporting the goals of accurate PA tracking and improved individualization of clinical interventions.

1. Introduction

Post-menopausal women aged 50 years and older are four times more likely to experience osteoporosis than men [1,2] and are at a high risk of fractures due to decreased bone mineral density (BMD) [1,3]. Of these women, approximately 1 in 5 who sustain hip fractures will require long-term care [4], resulting in reduced quality of life [5] and incurring significant financial burden [6]. Increasing physical activity (PA) in daily life, especially through activities which increase loading along the load-bearing axis (including feet, legs, hips and trunk), is expected to provide clinically relevant hip BMD increases [7,8] and is often cited as an intervention target. Previous work by our group [9] and others [10–12] have demonstrated positive correlations of peak vertical accelerations (pVacc), measured with body-worn

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https://doi.org/10.1016/j.gaitpost.2019.01.021
Received 31 January 2018; Received in revised form 4 December 2018; Accepted 14 January 2019
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accelerometers, with peak dynamic forces produced along the vertical axis (peak vertical ground reaction forces (pVGRFs)) during laboratory-based gait in healthy children, and young and middle-aged adults. Our previous work yielded the strongest correlations when using ankle-worn accelerometers and demonstrated their potential for estimating dynamic loading passively during PA [9]. However, a well-defined relationship between heel-strike acceleration and dynamic loading has not yet been determined in older adults.

The aim of the current study is to expand our dynamic loading estimation model to post-menopausal women so that their pVGRFs and joint loading can be estimated indirectly. Assessing PA using accelerometry, however, is challenged by varying gait velocities, especially at the lower end of walking speeds [13–15]. As lower walking speeds are often associated with aging individuals, and are considered a fall risk predictor [16], special consideration must be taken to ensure our observed relationship among pVGRF and pVacc are valid for the walking velocity range typically observed in post-menopausal women. We hypothesized that, based on our previous observations [9], we would observe a similar trend of strong correlation among pVGRFs and pVaccs in the heel-strike region (i.e. during loading response), captured using ankle-worn sensors, regardless of walking velocity.

2. Methods

Seventy post-menopausal women participated in this study, with a mean (SD) age of 61.3 (7.4) years with a range of 46 to 79 years. Participants were required to be post-menopausal (i.e. without menses) for at least 1 year by self-report. Exclusion criteria included less than two years of self-reported starting, stopping or modifying osteoporosis treatment, currently taking prescription medication which may result in BMD changes, induced menopause, assistive walking device use or any lower body amputations or orthotics, a BMI of over 40 kg/m^2, prolonged bed rest, musculoskeletal performance deficits history, neuromotor impairment or hip surgery, lower-limb fracture, non-dominant hip or knee joint replacement, a current lower extremity injury, moderate to severe hip or knee arthritis, have undergone chemotherapy and long-term or current of corticosteroids use, self-reported history within the last five years of regular participation in impact or jumping exercises, and self-reported current smoker, or cardiovascular obstructive pulmonary disease including severe allergies or asthma. The mean (SD) BMI of participants was 25.9 (4.3) kg/m^2 (ranging from 18.4 to 39.9 kg/m^2), with a body mass of 69.8 (11.4) kg and height of 1.64 (0.06) m. The Mayo Clinic Institutional Review Board approved the study protocol and each subject provided written informed consent before participating.

Accelerometer data were captured using ActiGraph GT3X+ (ActiGraph LLC, Pensacola, FL, USA) activity monitors secured with straps around the ankle and located just above the lateral malleoli. Each axis was sampled at a rate of 100 Hz. Gait velocities were calculated for a minimum of 5 trials at each self-selected walking speed category (fast, normal and slow), recorded by photocells placed at either end of the walkway. GRF data were collected at 600 Hz from five force plates (AMTI Inc., Watertown, MA; Kistler Instruments, Winterthur, Switzerland), see Fig. 1. 2D video was acquired at a rate of 60 Hz for event verification with cameras facing the front and side of the force plate setup.

Accelerometer, force plate, and video data were collected as subjects each performed a minimum of 5 successful walking trials or as many trials as required to achieve 10 successful complete footfalls on a force plate at each of three self-selected walking speeds, barefoot similar to [11,17], in a straight line over a 30 m walkway (with additional room to accelerate and decelerate). For the initial set of trials, subjects were asked to walk at a self-selected normal gait velocity. Subjects were then given verbal feedback to speed up or slow down for the following sets of trials, producing a range of self-selected walking velocities (Table 1).

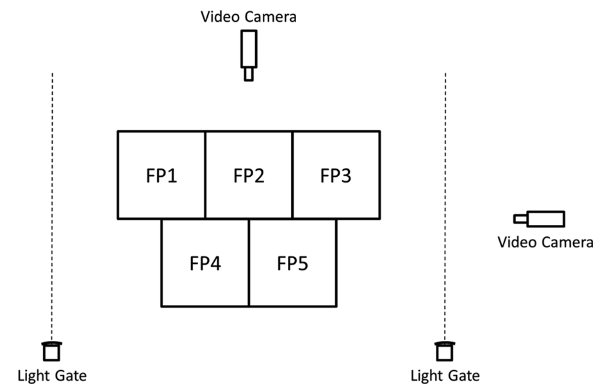

Fig. 1. Participant walkway configuration for data collection including 5 force plates (FP1-5), two light gates and two video cameras to capture gait kinetics, velocity and determine stepping events. Participants alternated walking directions between trials, walking towards either FP1/4 or FP3/5, through both light gates, along the 30 m walkway.

Table 1
Mean (SD) walking velocity, body weight-normalized peak vertical ground reaction forces (pVGRFbw) and peak vertical ankle acceleration (pVacc) for each self-selected walking speed. All comparisons were significantly different at $p < 0.01$ with Bonferroni corrections.

Walking Speed (Self-selected)	Walking Velocity (m/s)	pVGRFbw (N/BW)	pVacc (*g*)
Fast	1.659 (0.261)	1.204 (0.121)	3.536 (0.723)
Normal	1.394 (0.210)	1.116 (0.101)	2.956 (0.558)
Slow	1.079 (0.187)	1.028 (0.061)	2.355 (0.438)

All post-processing of accelerometer and force plate data were performed offline using MATLAB 2016b (Mathworks, Natick, MA, USA). Video data were analyzed to determine which steps corresponded to the force plate strikes for each trial so that accelerometer and force plate data corresponding to those steps could be determined. Force plate data were collected for one to five steps per trial. No subject achieved more than three successful complete footfalls on a force plate during any one trial. A total of 1122 trials were recorded, resulting in 2773 observed footfalls providing simultaneous observations of pVacc and pVGRFs in the heel-strike region. pVGRFs (normalized to body weight, pVGRFbw) were determined from the force plate data by measuring the first vertical impact peak's value. Due to data loss, only 2438 footfalls had usable walking velocity (Vel$_w$) data.

Heel-strike acceleration regions were detected visually from graphical representations of the vertical ankle-worn acceleration data. The maximum vertical acceleration point in the heel-strike region (i.e. during loading response) was taken as pVacc. All steps where it was determined visually using video data that 100% of the foot contact with the ground occurred within a single force plate were included in the analysis.

2.1. Statistical analyses

A set of linear mixed-models (LMMs) for repeated measures with diagonal variance-covariance structures were performed to identify differences among measured walking velocity (Vel$_w$), pVGRFbw and pVacc between the instructed three levels of walking speeds (*Fast, Normal,* and *Slow*). These analyses provided confidence that a range of significantly different walking behaviors were captured during data collection by assessing whether these self-selected walking speed categories were statistically different from one another. Bonferroni adjustments were adopted to evaluate post-hoc comparisons, when necessary.

LMMs for repeated measures were also employed to develop predictive models of pVGRFbw, including pVacc, Vel$_w$ and age as predictors, as well as subject as a random intercept. Including subject as random intercept assists to alleviate issues of non-independence stemming from multiple observations per subject, as is the case in this experimental design. All variables were input as continuous measures to best capture the variability in individual performance and impact of participant age in the population sample.

Three increasingly parsimonious models relating pVGRFbw with pVacc, Vel_w and age were generated in a step-wise fashion to identify significant predictors, where significance was defined as alpha = 0.05 for all tests. Marginal and conditional coefficients of determination [18] (R_M^2; the variance explained by the fixed effects in a mixed-model, and R_C^2; the variance explained by both the fixed and random effects in a mixed-model) were calculated for each LMM to capture an estimate of explained variance in the sampled population. Chi-squared (χ^2) tests were used to test for significant improvements in model fit among mixed-models. Visual inspection of the frequency and residual distributions of these models showed little infringement upon assumptions of normality or homoscedasticity, therefore no data transformations were performed.

$$\text{LMM Model 1: } pGRFbw = \propto + \beta_1 pVacc + \beta_2 Vel_w + \beta_3 Age + \varepsilon \quad (1)$$

$$\text{LMM Model 2: } pGRFbw = \propto + \beta_1 pVacc + \beta_2 Vel_w + \varepsilon \quad (2)$$

$$\text{LMM Model 3: } pGRFbw = \propto + \beta_1 pVacc + \varepsilon \quad (3)$$

Where α represents the random intercept included to account for between subject variation and non-independence of repeated samples.

To estimate out-of-sample prediction accuracy, block sampled, k-folds cross-validation analysis (5 folds, approximately 14 subjects per fold) was performed, without replacement, to quantify mean-absolute-error (MAE) and root-mean-square error (RMSE). Confidence intervals were compared among models to interpret differences in prediction accuracy. Bland-Altman plots [19,20] were generated to observe the distribution of average differences between the model predicted and “gold standard” estimates of pVGRFbw collected via force plate measure for each model. Bootstrap re-sampling with replacement was performed 1000 times to estimate confidence intervals for the repeated measures correlation [21] among pVGRFbw and the predictor variables. All statistical analyses were performed in R 3.4.1 [22].

3. Results

Mean walking velocities ($F_{2,1048.1} = 3076.6$, $p < 0.05$), pVGRFbw ($F_{2,2704.2} = 1903.6$, $p < 0.05$) and pVacc ($F_{2,2704.1} = 2364.9$, $p < 0.05$) were observed to be significantly different among *Fast, Normal,* and *Slow* self-selected walking speeds (Table 1). A repeated measures correlation coefficient and scatterplot (Fig. 2) suggested a strong linear relationship ($r = 0.747$, $p < 0.01$, 95% CI [0.729–0.764]) between pVGRFbw and ankle pVacc. Significant correlations were also observed among pVGRFbw and Vel_w ($r = 0.795$, $p < 0.01$, 95%CI[0.773–0.805]) and age ($r = -0.11$, $p < 0.01$, 95%CI[−0.14 to −0.07]).

In Model 1, *age* was not found to be a significant predictor of pVGRFbw ($t_{69.2} = -0.42$, $p = 0.676$) and was removed from subsequent analyses. Due to the limited influence of *age*, Model 1 and Model 2 yielded similar coefficients of determination, approximately 0.62 and 0.78 for R_M^2 and R_C^2, respectively, and were not significantly different ($\chi^2(1) = 0.176$, $p = 0.675$). Dropping Vel_w in Model 3 significantly decreases the fit of the model ($\chi^2(1) = 606.2$, $p < 0.001$), yielding 0.52 and 0.73 for R_M^2 and R_C^2, respectively. Most of the variability in pVGRFbw can be attributed to *pVacc* (52%), and further explained by the inclusion of Vel_w (approximately 10% R_M^2 change). The results of the step-wise evaluation of significant predictors of pVGRFbw are summarized in Table 2.

Out-of-sample predictive performance after 5-folds cross-validation is summarized in Table 3, below. Model 2 shows the lowest error rate among the generated models with 5.98% [5.61–6.42] MAE and 0.076BW [0.069–0.082] RMSE, however does not appear to appreciably improve prediction accuracy over the simpler Model 3 (6.80%), as evidenced by the overlapping confidence intervals.

Bland-Altman plots (Fig. 3) were generated for Models 2 and 3. Model 3 shows slightly larger limits of agreement compared to Model 2, suggesting decreased prediction accuracy, which is expected considering the increase in MAE between Model 2 and 3. In Model 3, prediction accuracy decreases as the magnitude of the measurement (pVGRFbw) increases. Across both models, very little mean bias is observed, as the average difference and their 95% limits of agreement are 0.00 [−0.111 to 0.111] and 0.00 [−0.125 to 0.125] for Models 2 and 3, respectively.

4. Discussion

Bone and joint loading accomplished through PA is a frequently cited target for improving bone health [23,24]. In previous work, we have shown the application of low-cost ankle-worn accelerometers to be effective predictors of lower-limb loading during lab-based walking and jogging trials, however these results were limited to 9 healthy young and middle-aged individuals [9]. To expand these results to a larger, at-risk, population, the current study investigated predictive relationships of pVGRFs produced during volitional walking considering pVacc, Vel_w and age in a cohort of post-menopausal women. Using a step-wise approach, three increasingly parsimonious models were generated to identify significant predictors of pGRFbw and estimate prediction accuracy using k-folds cross-validation techniques. We have shown that a mixed-effects model including only pVacc measured at the ankle shows comparable pVGRFbw prediction (Model 3 MAE: 6.80% [6.37–7.54]) with a more complex model including walking velocity (Vel_w) (Model 2 MAE: 5.98 [5.61–6.42]). Age was not found to be a significant predictor of pVGRFbw within this population. These

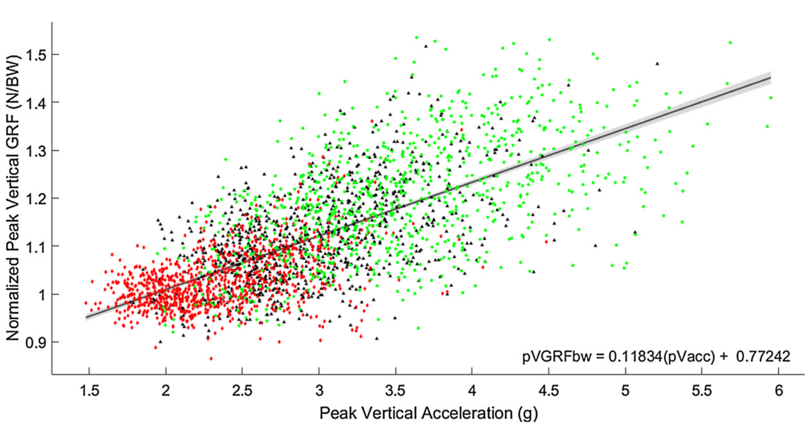

Fig. 2. Peak vertical acceleration (pVacc) vs body weight normalized peak vertical ground reaction forces (pVGRFbw) for each self-selected walking speed category: *Fast* walking in green (circle) *Normal* walking in black (triangle) and *Slow* walking in red (diamond). The regression line (black) and standard error of the regression (shaded area) are provided, based on fixed-effects in Model 3 and the average value of the random intercept for the population.

Table 2
Step-wise evaluation of significant predictors of pVGRFbw, generating a more parsimonious model.

Fixed Effects	Intercept (α)	Estimate (β_i)	SE	df	t-value	Pr (> |t|)	R_M^2	R_C^2
LMM Model 1							**0.619**	**0.776**
Intercept	0.7306		0.0506	72.10	14.44	< 0.001		
Peak vertical acceleration (pVacc)		0.0422	0.0035	2438	12.20	< 0.001		
Age		−0.0003	0.0008	69.2	−0.42	0.676		
Walking velocity (Vel_w)		0.2062	0.0079	2438	26.25	< 0.001		
LMM Model 2							**0.615**	**0.775**
Intercept	0.7097		0.0085	267.8	83.83	< 0.001		
Peak vertical acceleration (pVacc)		0.0422	0.0035	2437	12.20	< 0.001		
Walking velocity (Vel_w)		0.2063	0.0079	2438	26.25	< 0.001		
LMM Model 3							**0.516**	**0.732**
Intercept	0.7724		0.0095	207.1	81.23	< 0.001		
Peak vertical acceleration (pVacc)		0.1183	0.0020	2432	55.10	< 0.001		

Note: R_M^2 and R_C^2 represent the marginal and conditional coefficients of determination.

Table 3
Mean absolute error percentage (MAE%) and root mean square error (RMSE) estimates describing out-of-sample prediction accuracy using k-folds cross validation. 95% confidence intervals are provided for comparison.

Model	MAE (%)	RMSE (BW)
Model 2	5.98 [5.61–6.42]	0.076 [0.069–0.082]
Model 3	6.80 [6.37–7.54]	0.087 [0.081–0.095]

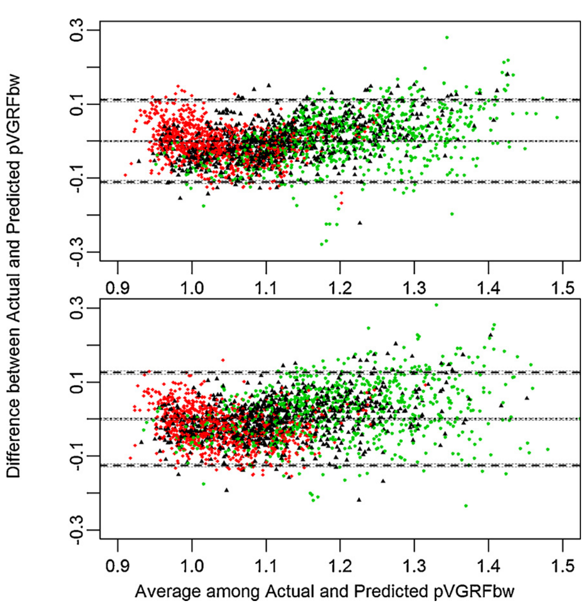

Fig. 3. Bland-Altman plots showing the paired differences against the average of measured pVGRFbw and model estimates. Subplots A and B represent Models 2 and 3, respectively. Mean bias and limits of agreement are shown with bolded dashed lines, while confidence intervals are shown by dotted lines for each. Green (circle), black (triangle) and red (diamond) comparisons represent *Fast*, *Normal* and *Slow* self-selected walking speeds, respectively.

results provide support for the use of ankle-mounted accelerometers alone for the tracking and augmentation of daily PA, providing new techniques to assess the dynamic body loading associated with these activities.

The step-wise modelling, bootstrap re-sampling and cross-validation techniques employed provide greater confidence to the strength and application of these findings, yielding a narrow 95% confidence interval and a low average out-of-sample prediction error while achieving a simplified model (Table 3). The MAE and RMSE of the most simplified model (Model 3) observed in our broad population of post-menopausal women (6.80% [6.37–7.54] and 0.087BW [0.081-0.095] respectively) were comparable to our previous study on young to middle-aged adults [9], and slightly lower than the MAE (8.3%) estimated from hip acceleration measured in healthy individuals [25] using similar linear regression techniques.

Model exploration using mixed-modelling techniques provided insight into the variability sources which are attributable to experimental predictors versus individual differences among participants. Across the observed models, the MAE and RMSE rates are consistently low, however the explained variance changed dramatically. When accounting for between-subject differences using mixed-modelling techniques, we observed high conditional coefficients of determination (R_C^2), upwards of 77.5% in Model 2 and 73.2% in Model 3. The more complex Model 2, which included objective measures of gait velocity, also demonstrated increased model fit corresponding to their fixed-effects (represented by the marginal R^2) yielding R_m^2 estimates of 61.5% versus the 51.6% for Models 3. Here, we see approximately 10.3% more variance explained with the inclusion of Vel_w in a predictive model of pVGRFbw between Model 2 and Model 3. These results show that Vel_w is significantly related to pVGRFbw, and that a significant portion of the variability observed in this population is related to individual differences in performance (Table 2). The individual data points grouped by self-selected walking speed categories in Fig. 2, and the increasing standard deviations observed in Table 1, highlight the increased variability among the self-selected *Fast* and *Normal* walking speed trials, relative to *Slow* walking speed, in both the pVGRFbw and pVacc. This variability results from individual interpretations of *Fast* and *Normal* walking speeds, where, in some cases, the fastest observed walking speed of one participant barely reached the average self-selected *Normal* walking speed for the population.

Other noise sources may have included reduced sensor fixation quality due to ankle anthropomorphics in some participants, resulting in exaggerated accelerations or other motion artifacts. BMI was not included in model analyses as pVGRF measurements were normalized to body mass to account for differences among participants. Targeting behavior was occasionally observed during walking, where participants would adjust their walking direction or speed as they approached the force-plates. Although effort was taken to identify and exclude these trials prior to analyses, this laboratory-induced behavior may have added to noise.

To explore potential bias in the model estimates of pVGRFbw, Bland-Altman plots were generated, taking special care to account for repeat observations among subjects [19,26]. No mean biases were observed in models 2 or 3, which were centered with 95% confidence intervals around 0.0. There is, however, conflicting information in the literature suggesting the use of Bland-Altman plots for the evaluation of regression predictions during cross-validation [27], but evaluation of the mixed-models residuals showed no structure during model generation. These results suggest strong agreement among the predicted and measured pVGRFbw estimates. When measures of walking velocity and pVacc are both available, estimates of lower-limb loading will contain less error than those based on pVacc alone (approximately 5.98% instead of 6.80%, on average). Measuring Vel_w outside of the laboratory is challenging with current wearable sensor technology which typically rely on anthropomorphic generalizations and integration methods susceptible to drift [28,29]. Recent work using machine learning to estimate walking velocity shows promise [30], however, the results of this study support the use of measures of pVacc at the ankle alone to provide comparable estimates pVGRFbw.

Finally, although including only barefoot walking may limit generalizability in the many shod configurations of daily living, older women tend to spend much of their time unshod and indoors [31,32]. Previous studies have reported conflicting results concerning peak GRF differences between barefoot and shod conditions [33], none have investigated whether differences exist in the pVacc and GRF relationship. In an attempt to investigate the effect of shoes, we applied Model 2 from the current study to our previously collected dataset of nine younger adults wearing athletic shoes [9]. The MAE of predictions increased from 6.05% to 10.2% and RMSE from 0.078BW to 0.128BW when the older post-menopausal women model (Model 2) predicting pVGRFbw was applied to the younger participant dataset. While these MAE and RMSE differences could be attributed to unshod versus shod conditions, there are a number of additional study design differences to consider such as sample size (70 versus 9), the inclusion of unnatural shuffling steps, to simulate very slow walking speeds, and jogging in the younger adult study, the number of samples (2438 versus 169), as well as potential unaccounted for population-related differences. Furthermore, the increase in MAE to 10.2% falls within the previously reported range of 5.2–13.5% in younger adults [12,27]. Finally, smaller peak acceleration and GRF differences have been reported when comparing barefoot to street shoes rather than athletic shoes [33] which may be less regularly worn by older women.

Given the suggested large duration of time spent unshod indoors at home by older women [31,32] and the reasonable although slightly larger MAE in GRF prediction when applying the current study's most complex model (Model 2) to our previously published shod younger-adults data, the current study's results provide valuable information on the pVacc and pVGRFbw relationship in post-menopausal women. The potential effect of shod walking needs to be investigated in post-menopausal women in future work. This study is the first to show a strong relationship among low-cost and easily obtainable ankle accelerometry data and high fidelity lower-limb loading approximations in post-menopausal women. This relationship provides us with the first step necessary to estimate real-world limb and joint loading, with and without the need for estimates of walking velocity, for the purposes of accurate PA tracking and improved individualization of clinical interventions.

Funding

Funding for this project was provided by the Mayo Clinic Robert D. and Patricia E. Kern Center for the Science of Health Care Delivery and the National Institutes of Health (R21 AR066643).

Conflict of interest disclosure

None of the authors has a conflict of interest to declare, and all authors were involved in the study design, data collection and interpretation, and contributed to the writing of the manuscript. This manuscript is not currently being considered for publication by another journal.

Acknowledgements

Research reported in this publication was supported by the National Institute of Arthritis and Musculoskeletal and Skin Diseases of the National Institutes of Health under Award Number R21 AR066643 and Robert D. and Patricia E. Kern Center for the Science of Health Care Delivery. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. Subject recruitment and data collection were performed by Stacy Loushin and Christine Huyber from the Mayo Clinic Motion Analysis Lab.

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