Osteoporosis International

# Accelerometer-based prediction of skeletal mechanical loading during walking in normal weight to severely obese subjects

--Manuscript Draft--

| | |
|---|---|
| **Manuscript Number:** | OSIN-D-19-00652 |
| **Full Title:** | Accelerometer-based prediction of skeletal mechanical loading during walking in normal weight to severely obese subjects |
| **Article Type:** | Original Article |
| **Funding Information:** | European Regional Development Fund (POCI-01-0145-FEDER-016707) — Not applicable<br>European Regional Development Fund (UID/DTP/00617/2019) — Not applicable<br>Fundação para a Ciência e a Tecnologia (PTDC/DTP-DES/0968/2014) — Not applicable<br>Fundação para a Ciência e a Tecnologia (SFRH/BD/117622/2016) — Mr. Florêncio Diniz-Sousa |
| **Abstract:** | Introduction: Currently, there is no way to objectively prescribe and monitor exercise for bone health improvement in obese patients based on mechanical loading intensity. Our aim was to develop accelerometry-based equations to predict peak ground reaction forces (pGRF) on normal weight to severely obese subjects. Methods: Sixty-four subjects (45 females; 84.6±21.7kg) walked at different speeds (2, 3, 4, 5 and 6 km.h-1) on a force plate equipped treadmill while wearing accelerometers at ankle, lower back and hip. Regression equations were developed to predict pGRF from accelerometry data. Leave-one-out cross-validation was used to calculate prediction accuracy and Bland-Altman plots. Actual and predicted pGRF at different speeds were compared by repeated measures ANOVA. Results: Variables included in the final equations were body mass and peak acceleration. Our results showed that the coefficients of determination on all equations were above 0.89 and that Bland-Altman plots indicated a good agreement between actual and predicted pGRF. All models presented an accurate prediction, with a mean absolute percent error (MAPE) below 6.7% and a root mean square error below 104.1N. No significant differences were observed between actual and predicted pGRF for each walking speed. Accuracy indices from our equations were lower than previously developed equations for normal weight subjects, namely a MAPE approximately 3 times smaller, lower dispersion Bland-Altman plots and bias tending to zero. Conclusion: Walking pGRF in normal weight to severely obese subjects can be accurately predicted by accelerometry-based equations, representing an easy and accessible way to determine mechanical loading intensity in clinical settings. |
| **Corresponding Author:** | Lucas Veras<br>Faculty of Sports, University of Porto<br>PORTUGAL |
| **Corresponding Author Secondary Information:** | |
| **Corresponding Author's Institution:** | Faculty of Sports, University of Porto |
| **Corresponding Author's Secondary Institution:** | |
| **First Author:** | Lucas Veras |
| **First Author Secondary Information:** | |
| **Order of Authors:** | Lucas Veras<br>Florêncio Diniz-Sousa<br>Giorjines Boppre<br>Vítor Devezas |

| | |
|---|---|
| | Hugo Santos-Sousa |
| | John Preto |
| | João Paulo Vilas-Boas |
| | Leandro Machado |
| | José Oliveira |
| | Hélder Fonseca |
| **Order of Authors Secondary Information:** | |
| **Author Comments:** | |
| **Suggested Reviewers:** | Damian Raper<br>damian.raper@gmail.com |
| | Victoria Stiles<br>v.h.stiles@exeter.ac.uk |

# Accelerometer-based prediction of skeletal mechanical loading during walking in normal weight to severely obese subjects

Lucas Veras[a], Florêncio Diniz-Sousa[a], Giorjines Boppre[a], Vítor Devezas[b], Hugo Santos-Sousa[b], John Preto[b], João Paulo Vilas-Boas[c,d], Leandro Machado[c,d], José Oliveira[a], Hélder Fonseca[a]

a - Research Center in Physical Activity, Health and Leisure (CIAFEL), Faculty of Sport, University of Porto, Porto, Portugal

b - General Surgery Department, São João Medical Center, Porto, Portugal

c - Center of Research, Education, Innovation and Intervention in Sport (CIFI2D), Faculty of Sport, University of Porto, Porto, Portugal

d - Biomechanics Laboratory (LABIOMEP-UP), University of Porto, Porto, Portugal

Corresponding author name: Lucas Veras

Mailing address:

Faculty of Sport, University of Porto

Rua Dr. Plácido Costa, 91

4200-450 Porto, Portugal

Telephone: +351 220425202

Fax: +351 2255006867

E-mail: lucasdsveras@gmail.com

Lucas Veras - ORCID Number: 0000-0003-0562-5803

Florêncio Diniz-Sousa - ORCID Number: 0000-0001-9042-383X

Giorjines Boppre - ORCID Number: 0000-0003-2974-6343

Vítor Devezas - ORCID Number: 0000-0003-1032-4474

Hugo Santos-Sousa - ORCID Number: 0000-0001-6176-5654

João Paulo Vilas-Boas - ORCID Number: 0000-0002-4109-2939

Leandro Machado - ORCID Number: 0000-0001-5332-5974

José Oliveira - ORCID Number: 0000-0002-1829-4196

Hélder Fonseca - ORCID Number: 0000-0002-9002-8976

**Conflict of interest**

Lucas Veras, Florêncio Diniz-Sousa, Giorjines Boppre, Vítor Devezas, Hugo Santos-Sousa, John Preto, João Paulo Vilas-Boas, Leandro Machado, José Oliveira and Hélder Fonseca declare that they have no conflict of interest.

**Acknowledgements**

This study was funded by the Foundation for Science and Technology of Portugal (FCT) (grant PTDC/DTP-DES/0968/2014) and by the European Regional Development Fund (ERDF) through the Operational Competitiveness Programme (COMPETE) (grant POCI-01-0145-FEDER-016707). Florêncio Diniz-Sousa was supported by the FCT (grant SFRH/BD/117622/2016). The study was developed in the Research Centre in Physical Activity, Health and Leisure (CIAFEL) funded by ERDF through the COMPETE and by the FCT (grant UID/DTP/00617/2019). The authors would like to thank the participants who took part in this research and all that have collaborated in the project.

**Summary**

There is no objective way to monitor mechanical loading intensity during exercise for bone health improvement. We developed accelerometry-based equations to predict ground reaction force (GRF) in normal weight to severely obese subjects. These equations proved to accurately predict GRF, representing an easy way to determine intensity in clinical settings.

**Abstract**

**Introduction:** Currently, there is no way to objectively prescribe and monitor exercise for bone health improvement in obese patients based on mechanical loading intensity. Our aim was to develop accelerometry-based equations to predict peak ground reaction forces (pGRF) on normal weight to severely obese subjects. **Methods:** Sixty-four subjects (45 females; 84.6±21.7kg) walked at different speeds (2, 3, 4, 5 and 6 $km \cdot h^{-1}$) on a force plate equipped treadmill while wearing accelerometers at ankle, lower back and hip. Regression equations were developed to predict pGRF from accelerometry data. Leave-one-out cross-validation was used to calculate prediction accuracy and Bland-Altman plots. Actual and predicted pGRF at different speeds were compared by repeated measures ANOVA. **Results:** Variables included in the final equations were body mass and peak acceleration. Our results showed that the coefficients of determination on all equations were above 0.89 and that Bland-Altman plots indicated a good agreement between actual and predicted pGRF. All models presented an accurate prediction, with a mean absolute percent error (MAPE) below 6.7% and a root mean square error below 104.1N. No significant differences were observed between actual and predicted pGRF for each walking speed. Accuracy indices from our equations were lower than previously developed equations for normal weight subjects, namely a MAPE approximately 3 times smaller, lower dispersion Bland-Altman plots and bias tending to zero. **Conclusion:** Walking pGRF in normal weight to severely obese subjects can be accurately predicted by accelerometry-based equations, representing an easy and accessible way to determine mechanical loading intensity in clinical settings.

**KEY-WORDS:** force plates; raw acceleration; gait; mechanical loading; activity monitor.

## Introduction

Obesity is an increasingly prevalent problem worldwide [1] due to metabolic, cardiovascular and oncologic diseases associated with and reduced life expectancy [2]. Despite the first studies investigating the effects of obesity on bone mass showed that higher body mass was associated with higher bone mass [3], more recently, both mechanistic [4,5] and epidemiological evidence suggests that obesity compromises bone quality [6-8] and increases fracture risk [9-11]. Exercise is, in this context, a valuable aid in the management of obesity [12], its related cardio metabolic complications [13,14], and for improving bone health [15].

However, not all forms of exercise produce equal bone health benefits [16,17], and a major limitation in this context is the inability to accurately control skeletal mechanical loading intensity. In addition, patients with obesity frequently have chronic joint pain [18], complicating further the prescription of impact exercise that has both osteogenic potential and a low probability of inducing joint discomfort. Since there is no way to currently control skeletal mechanical loading in the clinical setting, exercise prescription and monitoring is mostly done blindly, without a way to gauge the dose-response relationship between exercise and bone health outcomes.

Accelerometers, small wearable devices that measure body accelerations (ACC), have been broadly used to objectively monitor physical activity levels [19,20] and its relation with cardiovascular and metabolic health outcomes [21]. More recently, accelerometers have started to be explored as a way to measure skeletal mechanical loading [22] by estimation of ground reaction forces (GRF) [23]. Force plates (FP) are the gold standard for GRF measurement [24] but are unsuitable for GRF determination in clinical settings. Considering their accuracy, portability and low cost, accelerometers have been proposed as ideal candidates to predict peak GRF (pGRF) in clinical settings [25-28], providing a way to monitor exercise-induced mechanical loading and therefore adequate exercise prescription and monitoring for improvement of bone health [17]. However, body mass is an important variable for ground reaction force prediction [27,26,25]. Therefore, despite initial studies have showed promising results in accelerometer derived pGRF prediction, these results are only valid for a limited body mass range (≈ 50 – 90 kg) [28,27] leaving most patients with overweight and obesity out of accelerometry-based predictive equations.

Considering the prevalence of obesity [29], its associated fracture risk [9-11] and that these patients are especially prone to develop loading associated musculoskeletal injuries [30], there is a need to develop GRF prediction equations that are accurate for overweight and obese subjects in order to precisely determine and monitor exercise-associated mechanical loading in these patients. Therefore, the purpose of this study was to develop prediction equations based on accelerometer data able to accurately predict GRF on a broad range of body masses, from normal weight to severely obese subjects, setting thereby, a base for objective prescription and monitoring of exercise mechanical loads.

**Methods**

A 64 adult convenient sample with body mass ranging from 51.4 to 152.5 kg (19 males, 45 females; age: 34.9±11.6 yrs; height: 162.8±9.6 cm; body mass: 84.6±21.7 kg; body mass index (BMI): 32.3±9.3 $kg \cdot m^{-2}$; $\bar{X}$±SD) were recruited for this study. All participants presented no self-reported neurological impairments and were free from orthopedic or musculoskeletal limitations. Participants were informed about the purpose and protocol of the experiment before giving their written informed consent. The study was approved by the local Ethics Committee.

Data collection took place at Porto Biomechanics Laboratory (LABIOMEP-UP), in an instrumented front-back split-belt treadmill with built-in FPs (AMTI Corporation, Watertown, MA, USA). Before starting the protocol, all participants performed a practice walking on the instrumented treadmill to get familiarized with the testing procedure. The protocol consisted of walking in several incremental speeds, in the following order: 2, 3, 4, 5 and 6 $km \cdot h^{-1}$ (0.56, 0.83, 1.11, 1.39, 1.67 $m \cdot s^{-1}$). Our experience shows that the utilization of progressive incremental speeds improves the patient's familiarization with the treadmill, which is of particular importance in severely obese patients unaccustomed to perform these tasks. Each speed lasted 1 minute with no rest time among speeds. Participants were asked to look straight ahead while walking and were not allowed to hold handrails. To ensure single foot contact on each FP during the trial, participants were provided with feedback as to their location on the instrumented treadmill by a researcher. All participants wore their own sports shoes throughout the trials.

During the protocol, participants wore three activity monitors, one at their right hip (along the anterior axillary line, at the level of the iliac crest), another at their lower back (at the midpoint between the two posterior superior iliac spines) and the last at their right ankle (immediately superior to the lateral malleolus). Activity monitors at

waist level were secured on the same elastic belt with a clip and the activity monitor placed on the ankle was secured by an elastic belt fixed with adhesive tape. In all placements the accelerometer y-axis (vertical) was aligned with the longitudinal axis of the body, taking into account a standing position. All participants wore the same three activity monitors always positioned at the same places.

Activity monitors used were the GT9X Link model (3.5 X 3.5 X 1.0 cm, 14 g; ActiGraph, Pensacola, FL, USA) that incorporates a primary and a secondary triaxial accelerometers. Because the manufacturer software automatically applies a proprietary filter on the primary accelerometer raw data, but not on the secondary accelerometer raw data, only data from this latter was utilized in this study. This option reduces any filtering-induced bias and offers more transparency to our data processing allowing, therefore, higher replicability.

The software supplied by the manufacturer was used to initialize the accelerometers and download the data (ActiLife version 6.13.3; Actigraph, Pensacola, FL, USA). Sampling frequency was set at 100 Hz. Raw ACCs from x, y and z components (expressed in gravity acceleration units; 1 $g$ = 9.807 $m \cdot s^{-2}$) were exported to a comma-separated values file format (.csv extension). FP data were collected at a 1000 Hz sampling frequency, operated through the manufacturer-supplied software (Netforce, Version 3.5.1; AMTI Corporation, Watertown, MA, USA). FP data were exported to a text file format (.txt extension).

FP and accelerometer recorded data were then further processed using MATLAB (Version 8.3, Mathworks, Natick, MA, USA) according with the following procedures: initially, to limit the GRF and ACC noise magnitude, data were filtered using a Butterworth fourth-order low-pass filter, with a 20 Hz cut-off frequency. Then, both ACC for each monitor and GRF resultant values were calculated ($r_i = \sqrt{x_i^2 + y_i^2 + z_i^2}$). After that, peak ACC (pACC) values were defined as having a minimum height of twice the positive ACC average, during a given walking speed, and being separated by a minimum of 0.4 seconds. FP and accelerometers data were then synchronized using the following sequential steps: i) signal adjustment through the time set by the systems clock; ii) manual correction based on visual inspection for possible errors in time adjustment; iii) determination of pGRF as the highest values between 0.4 seconds before and after each pACC; iv) synchronization by the maximum cross-correlation coefficient of FP and accelerometer peak values for both the resultant and its vertical component. This synchronization process ensured a pGRF and pACC close to true matching. After that, the regions of interest for data analysis were manually selected where the walking patterns were constant, which corresponded of 30 to

45s period, on average. Then, pGRF and pACC mean of the resultant and its vertical component for each participant in each walking speed was extracted and used in all of the remaining analyses. A median of 47 peaks (interquartile range 34 to 63) were used to calculate the pGRF and pACC means.

Statistical analyses were conducted using R statistical software (version 3.5.2, R Foundation for Statistical Computing, Vienna, Austria). All statistical analyses were registered in an open platform, where R code utilized for each analysis is described and more detailed information can be assessed [31].

Regression equations developed by linear mixed models (LMM) were used to predict peak resultant GRF (pRGRF) and peak vertical GRF (pVGRF). Distinct LMM were developed with data from accelerometers placed at the ankle, lower back and hip. Covariance structure used was an autoregressive process of order 1 and maximum likelihood method was used for estimating parameters. This covariance structure has been proposed as the most adequate for repeated-measures data such as ours [32]. Predictors tested on pRGRF models were body mass (kg) and peak resultant ACC (pRACC; *g*), while on pVGRF they were body mass (kg) and vertical ACC (pVACC, *g*). All of them were tested as fixed effects and have shown to be significant predictors. Both random intercept and slopes were also tested, but only the random intercept inclusion has showed to improve the model. Linear, quadratic and cubic polynomial simulations were tested, but only the first two contributed significantly to the models. In opposition to what could be expected, speed was not included as a predictor since this variable is difficult to access continuously and reliably out of laboratory conditions. Therefore, its use would be hindered in prediction equations based on data from activity monitors recording habitual physical activity. Final models were chosen according to -2 log-likelihood statistics [32]. LMM analyses were conducted with nlme package (version 3.1-137). Traditional coefficient of determination ($R^2$) was represented by conditional $R^2$, computed with piecewiseSEM package (version 2.0.2), that estimates the variance explained by the whole model.

Model validation was assessed by the leave-one-out cross-validation (LOOCV) method. This approach is recommended when a different sample is not available for cross-validation and it provides an insight on the model potential to predict outcomes in a new independent sample [33]. For LOOCV each participant's data was separated into a testing dataset (one participant at a time) with the remaining data being in the training dataset. New LMM, with the same outcomes and predictors as determined for the entire sample, were developed using the training

dataset and then used to predict pGRF for the participant in the testing dataset. This process was repeated for all participants (64 times). Data from the testing dataset was used in the remaining statistical analysis.

Bland-Altman plots were used to examine the agreement between pGRF measured with FP and those predicted through the regression equations. The difference between the actual and predicted pGRF was plotted against their mean. Bias was expressed as the mean of these differences and the limits of agreement (LoA) were obtained using ±1.96 standard deviation of the mean between actual and predicted pGRF [34]. Linear regressions were applied to the data derived from each accelerometer placement and for each outcome (pRGRF and pVGRF) to identify if the magnitude of the mean between the actual and predicted pGRF influenced the magnitude of their difference, and, therefore, to determine if the prediction equation accuracy was constant throughout the assayed magnitude range. [35].

To evaluate the models prediction accuracy, mean absolute error (MAE), mean absolute percent error (MAPE) and root mean square error (RMSE) were calculated. Although there is no standard index nor threshold that defines what is an acceptable error for the GRF prediction, based on previous studies in this field [36,28,25], we considered an accurate prediction results that had a < 8% MAPE.

A series of repeated measures analysis of variance (ANOVA) were run to assess whether pGRF predicted from the regression equations were significantly different from those measured with FP. Walking speeds, accelerometer placements (ankle, lower back and hip), and the interaction effect (speed X accelerometer placements) were considered in the analysis. These procedures were taken separately for resultant and its vertical component. If assumptions of sphericity were violated ($p < 0.05$), the conservative Greenhouse–Geisser correction factor would be applied to adjust the degrees of freedom. Post-hoc analyses would be conducted using pairwise comparisons with Holm's test if a significant difference was observed among actual and predicted pGRF.

Our equation was posteriorly compared with a previously published reference equation [27], in which Neugebauer et al. used a similar approach for the prediction of pGRF. Comparison was performed using the equation to predict pVGRF from hip-worn accelerometers, as it was the only suitable with our data. The analysis was performed in three ways using: i) a subsample of participants with normal weight or overweight (BMI ≥ 18.5 and < 30 $kg \cdot m^{-2}$); ii) a subsample of obese participants (BMI ≥ 30 $kg \cdot m^{-2}$); iii) the whole sample. Bland-Altman plots were used to

confront the agreement between pVGRF measured with FP and those predicted using both regression equations. Also, to assess the prediction accuracy, MAE, MAPE and RMSE were calculated using pVGRF values predicted from both equations.

The statistically significant value was set as $\alpha = 0.05$.

**Results**

We first determined the relationship between pACC and pGRF obtained during the incremental walking speeds used in our experimental protocol. This was performed in order to verify the consistency of this relationship for increasing pACC values and the ability of the accelerometer to discriminate differences in pGRF between subjects in different BMI classes. A scatterplot with these relationships for all three accelerometer placements tested and for both the resultant and its vertical component is depicted in Figure 1. Generally, as expected, pACC recorded by accelerometers in all placements, showed a linear increase as a function of pGRF increases. Also, the recorded accelerations were shown to be able to provide a good discrimination between different BMI classes, as for the same registered pACC the pGRF tended to be consistently higher for subjects in higher BMI classes.

Afterwards we developed pGRF prediction equations based on pACC recorded by accelerometers in each placement and body mass as these were the only variables, of all those tested, that were shown to be significant predictors. Table 1 shows the regression equations developed from accelerometer placed at the ankle, lower back, and hip, their respective $R^2$ and accuracy indices. Our results show that, for all equations developed, $R^2$ values ranged between 0.89 and 0.95, with an average of 0.93, showing that all equations had a very good prediction ability. Also, MAE and MAPE were determined and were shown to range between 57.4 and 76.3 N, with an average of 66.8 N and between 5.4% and 6.7%, with an average of 6%, respectively, showing that our prediction errors were smaller compared to previously determined equations with MAPE ranging from 6.6% to 13.5% [28,27]. RMSE was also determined and was shown to range between 74.1 and 101.1 N with an average of 89.3 N. The approximately 33% higher average of RMSE compared to the average MAE suggests that our equations prediction ability was moderately affected by outliers. Of the several equations developed, the equation predicting pRGRF based on hip-worn accelerometers was the one that showed the best performance, with the highest $R^2$ (0.95) and the lowest MAE (57.4 N), MAPE (5.4%) and RMSE (74.1 N).

Then, Bland-Altman plots (Figure 2) were built in order to graphically determine the agreement between actual and predicted pGRF for both the resultant and its vertical component and for all the accelerometer placements. A good agreement is considered when values tend to cluster around zero, showing, therefore, that there is no trend for the equation to under or overestimate the actual pGRF. For all the prediction equations developed, values tended to aggregate mostly around zero and between the LoA, which corresponds to ± 1.96 SD. A trend for higher dispersion was observed in the pVGRF derived equations and mostly for participants with class III obesity. Again, the equation showing best performance and a higher degree of clustering around zero was the one derived from hip-worn accelerometers to predict pRGRF. To test the quality of the agreement, we performed a one-sample T test to assess if the bias was significantly different from zero. Results for all the equations showed that bias was not different from zero ($p > 0.05$), and, therefore, that our equations did not under or overestimate the actual pGRF. Moreover, to test if the prediction errors were systematically influenced by the pGRF magnitude, and, therefore, if the equations prediction accuracy was constant throughout the assayed magnitude range, linear regressions were determined. For lower back and hip placements, results showed a significant proportional bias ($p < 0.05$), however, with a low magnitude (highest $R^2 = 0.032$). These results suggest that despite there is a trend for underestimation at increasingly higher pGRF values, the magnitude of this effect is neglectable. No proportional bias ($p > 0.05$) was detected for ankle derived equations.

To investigate the existence of differences between the actual and predicted pGRF by all the equations developed and by all tested walking speeds, a repeated measures ANOVA was performed (Figure 3). Results demonstrated that, as expected, the actual and predicted pGRF increased significantly ($p < 0.001$) along with increments in walking speed and that there were no significant differences ($p > 0.05$) between actual and predicted pGRF in each speed. This shows that for all the equations, there were no significant differences between actual and predicted pGRF, within the range of tested walking speeds.

Finally, in order to match the prediction accuracy of our equation with a comparable reference equation in the literature, we calculated the accuracy indices (MAE, MAPE and RMSE) for Neugebauer's [27] equation using our data and compared it with our accuracy indices for the equation to predict pVGRF from hip-worn accelerometers (Table 2). Although this was not our equation with the best prediction performance, it was the only one comparable with Neugebauer's data. Results were expressed for the whole sample and according to

obese or non-obese classification, in order to compare the equations performance across different body masses. The accuracy indices from our equation were all substantially lower compared to the reference equation indices, with an overall MAPE approximately 3 times smaller for our equation. For both equations, the MAPE was lower in the obese subsample than in the non-obese subsample. Bland-Altman plots were also built to confront the different equations agreement between actual and predicted pGRF (Figure 4). A lower dispersion around the bias value, as well as a lower percentage of values falling off the LoA can be appreciated in our equation. Additionally, while the bias in our equation tended to be zero, in the reference equation bias was always > 0 ($p < 0.05$), showing a consistent underestimation of pVGRF.

**Discussion**

The purpose of this study was to develop prediction equations based on body-worn accelerometers to accurately predict GRF on subjects with a broad range of body masses, from normal weight to severe obesity, setting thereby, the basis for the objective prescription and monitoring of exercise mechanical loads for bone health improvement. We, therefore, tested the ability of accelerometers placed on different body locations to estimate ground reaction forces and the agreement between predicted and actually recorded ground reaction forces throughout different incremental walking speeds. Our results showed that raw ACC values obtained from different accelerometer placements, but especially from the hip, are well correlated with GRF throughout different walking speeds and that regression equations developed from accelerometer data are valid and accurate to predict pGRF during walking on a broad range of body masses.

All regression models developed showed an accurate prediction, below the 8% MAPE threshold established by us. For both the resultant and its vertical component, regression equations based on accelerometer placed on the hip showed the best prediction accuracy, with a MAPE around 5.5%. Equations based on lower back placement performed similarly to the hip in terms of pRGRF (5.5% MAPE), but with a slightly lower accuracy in the vertical component (6.6% MAPE). As for the equations based on the ankle placement, although they showed a higher MAPE compared with other accelerometer placements (around 6.5% for both resultant and its vertical component), they also presented an accuracy below the 8% MAPE threshold values. Moreover, for all accelerometer placements, equations to predict pRGRF revealed slightly better accuracy indices than the equations to predict pVGRF.

In addition to the small prediction error in our equations, our results showed a good agreement between actual and predicted pGRF, as represented by the Bland-Altman plots (Figure 2). Furthermore, repeated measures ANOVA (Figure 3) showed that when actual and predicted pGRF values were compared at each walking speed, no significant differences were observed, showing thereby that the prediction is accurately maintained throughout increasing walking speeds.

For a long time, accelerometers worn at the hip have been well accepted for energy expenditure and physical activity intensity predictions [19]. However, there are no well-defined accelerometer placements for pGRF prediction. Previous studies have suggested that, besides the hip [37,27,26,25], lower back [38] and ankle [28] could be good placements for accelerometer-based pGRF prediction. These assumptions are supported by our results. However, although all three placements have shown similar accuracy and have proved to be useful in the prediction of GRF, hip placement presented a slightly superior prediction accuracy among the three placements analyzed. This reinforces hip placement as the established location to measure physical activity by accelerometry even in obese or severely obese individuals.

Our data have also demonstrated that predictions could be made with both pVACC or pRACC, hence allowing pGRF prediction through both uni- or tri-axial accelerometers. Also, as the majority of GRF during walking seem to come from the vertical component, even those settings that have only access to uniaxial accelerometer data can obtain values of mechanical loading during walking. Nevertheless, prediction based on pRACC seems to offer an advantage, inasmuch as the predicted values do not depend on the accelerometer correct orientation, which is usually hard to guarantee outside laboratory conditions (i.e., measuring daily physical activity) [39,40].

Comparing our results with previous studies that used an analogous approach based on normal weight subjects only, shows that our accuracy indices derived from hip and ankle accelerometer placements were similar or even showed better accuracy. Considering hip placement, MAPE for pVGRF in our study was 5.7%, while formerly reported values ranged from 5.3% in military subjects with load carriage [25], to 8.3% in normal weight individuals [27,25]. Both our and previous results for pVGRF at ankle placement showed a MAPE around 6.5% [28]. No comparisons for pVGRF at lower back placement could be made due to the absence of similar previous studies. Nevertheless, MAPE of lower back placement was close to the results we obtained on the hip. Since this

is the first study to use pRACC to predict pRGRF, it is only possible to verify that our prediction models for pRGRF have a slightly smaller prediction error compared to the prediction models for pVGRF.

The slightly improved prediction observed in our study can be, at least partially, explained by the improved synchronization process used in our study which assured a very good matching between each pGRF and pACC measured by the force plate and accelerometer, respectively. Since other studies have used only pVGRF derived from a single step [27] or from an average of multiple steps [37,25] to match pVGRF with pVACC average, this procedure may have compromised the quality of the matching and, consequently, of the final prediction.

Besides validity, our regression equations surpass an important limitation of previous studies which is its applicability to a wide range of body masses. This was possible due to our large sample size, which encompassed subjects with BMI's ranging from normal up to class III obesity and body masses from 50 to 120 kg, with evenly distributed increments of approximately 2 kg within this range. Therefore, unlike previous studies that presented regression models working properly only on people around normal BMI [28,27,25], the present models are more robust, allowing an accurate walking pGRF prediction for the general adult population, including patients with overweight and obesity. Furthermore, this equation was developed in this body mass range using multiple walking speeds, thus, fully characterizing this type of locomotion, as recommended previously [27].

Until now, almost all studies that attempted to associate bone health[41] and injury[42] with human movement have used as parameter only ACC values. Vainionpää *et al*. [43] reported in their study that less than 100 mechanical loading events eliciting pVACC above 3.9 *g* (subtracting 1 *g* to account for the gravity ACC) per day were associated with an increase in proximal femur bone mineral density in premenopausal women. Yet, the use of ACC by itself entails an important limitation, since it only represents the ACC of a specific body segment and not a mechanical loading, which is a determinant factor for bone metabolism. Furthermore, mechanical loading expressed as force (in N) allows to directly compare results obtained by accelerometry data from different body placements. Therefore, future studies should aim to establish reference values for a given outcome based not in ACC, but in GRF, that can be easily and accurately estimated based on accelerometry data, as showed by our results.

The results of our study allow the estimation of skeletal mechanical loading based on accelerometry data and open thereby the possibility to monitor skeletal mechanical loading induced by exercise in clinical and field conditions. Nevertheless, advances are still needed in this area, such as expanding the prediction equations to non-locomotor activities with an adequate accuracy and determine the relationships between predicted GRF and surrogates of bone metabolism such as changes in bone mass or in biochemical markers of bone turnover. This would allow for researchers to precisely determine the dose-response relationship between exercise and bone health outcomes and to establish intensity thresholds, both in terms of effectiveness and safety, for a given bone health outcome.

Whilst the models presented here are valid, some limitations ought to be noted. First, the prediction models developed here are suitable for walking only, thus, not appropriate for other activities, such as running, jumping and activities with direction changing. Second, a different sample for model validation was not available. However, LOOCV was used, which is an advisable cross-validation method in these situations [33]. Third, evaluations were performed on an instrumented treadmill, which may induce some biomechanical changes in walking [44]. Nevertheless, although the use of a treadmill reduces external validity, at the same time it enhances the internal validity, as this equipment allows to accurately and continuously measure GRF [45]. Fourth, the same accelerometers were always positioned at the same places, which could not represent the overall population of monitors [39].

In conclusion, walking pGRF could be accurately estimated by regression equations based on accelerometry data. These prediction models are valid using resultant or just the vertical component acceleration obtained from ankle, lower back or hip accelerometer placement. These results will allow to easily obtain trustworthy pGRF data from accessible equipment's such as accelerometers enabling the objective prescription and monitoring of exercise mechanical loads in patients with increased fracture risk from normal weight to the severely obese.

# References


1. Collaboration NCDRF (2017) Worldwide trends in body-mass index, underweight, overweight, and obesity from 1975 to 2016: a pooled analysis of 2416 population-based measurement studies in 128.9 million children, adolescents, and adults. Lancet 390 (10113):2627-2642. doi:10.1016/S0140-6736(17)32129-3

2. Bluher M (2019) Obesity: global epidemiology and pathogenesis. Nat Rev Endocrinol 15 (5):288-298. doi:10.1038/s41574-019-0176-8

3. Khosla S, Atkinson EJ, Riggs BL, Melton LJ, 3rd (1996) Relationship between body composition and bone mass in women. J Bone Miner Res 11 (6):857-863. doi:10.1002/jbmr.5650110618

4. Roizen JD, Long C, Casella A, O'Lear L, Caplan I, Lai M, Sasson I, Singh R, Makowski AJ, Simmons R, Levine MA (2019) Obesity Decreases Hepatic 25-Hydroxylase Activity Causing Low Serum 25-Hydroxyvitamin D. J Bone Miner Res:e3686. doi:10.1002/jbmr.3686

5. Ramos-Junior ES, Leite GA, Carmo-Silva CC, Taira TM, Neves KB, Colon DF, da Silva LA, Salvador SL, Tostes RC, Cunha FQ, Fukada SY (2017) Adipokine Chemerin Bridges Metabolic Dyslipidemia and Alveolar Bone Loss in Mice. J Bone Miner Res 32 (5):974-984. doi:10.1002/jbmr.3072

6. Farr JN, Dimitri P (2017) The Impact of Fat and Obesity on Bone Microarchitecture and Strength in Children. Calcif Tissue Int 100 (5):500-513. doi:10.1007/s00223-016-0218-3

7. Kindler JM, Pollock NK, Ross HL, Modlesky CM, Singh H, Laing EM, Lewis RD (2017) Obese Versus Normal-Weight Late-Adolescent Females have Inferior Trabecular Bone Microarchitecture: A Pilot Case-Control Study. Calcif Tissue Int 101 (5):479-488. doi:10.1007/s00223-017-0303-2

8. Kim H, Lee SH, Kim BJ, Koh JM (2017) Association between obesity and femoral neck strength according to age, sex, and fat distribution. Osteoporos Int 28 (7):2137-2146. doi:10.1007/s00198-017-4015-2

9. Li X, Gong X, Jiang W (2017) Abdominal obesity and risk of hip fracture: a meta-analysis of prospective studies. Osteoporos Int 28 (10):2747-2757. doi:10.1007/s00198-017-4142-9

10. Rudman HA, Birrell F, Pearce MS, Tuck SP, Francis RM, Treadgold L, Hind K (2019) Obesity, bone density relative to body weight and prevalent vertebral fracture at age 62 years: the Newcastle thousand families study. Osteoporos Int 30 (4):829-836. doi:10.1007/s00198-018-04817-3

11. Kaze AD, Rosen HN, Paik JM (2018) A meta-analysis of the association between body mass index and risk of vertebral fracture. Osteoporos Int 29 (1):31-39. doi:10.1007/s00198-017-4294-7

12. Shaw K, Gennat H, O'Rourke P, Mar CD (2006) Exercise for overweight or obesity. Cochrane Database of Systematic Reviews (4). doi:10.1002/14651858.CD003817.pub3

13. Gleeson M, Bishop NC, Stensel DJ, Lindley MR, Mastana SS, Nimmo MA (2011) The anti-inflammatory effects of exercise: mechanisms and implications for the prevention and treatment of disease. Nat Rev Immunol 11 (9):607-615. doi:10.1038/nri3041

14. Ross R, Dagnone D, Jones PJ, Smith H, Paddags A, Hudson R, Janssen I (2000) Reduction in obesity and related comorbid conditions after diet-induced weight loss or exercise-induced weight loss in men. A randomized, controlled trial. Ann Intern Med 133 (2):92-103. doi:10.7326/0003-4819-133-2-200007180-00008

15. Fonseca H, Moreira-Goncalves D, Coriolano HJ, Duarte JA (2014) Bone quality: the determinants of bone strength and fragility. Sports Med 44 (1):37-53. doi:10.1007/s40279-013-0100-7

16. Schipilow JD, Macdonald HM, Liphardt AM, Kan M, Boyd SK (2013) Bone micro-architecture, estimated bone strength, and the muscle-bone interaction in elite athletes: an HR-pQCT study. Bone 56 (2):281-289. doi:10.1016/j.bone.2013.06.014
17. Turner CH, Robling AG (2003) Designing exercise regimens to increase bone strength. Exerc Sport Sci Rev 31 (1):45-50
18. Jinks C, Jordan K, Croft P (2006) Disabling knee pain--another consequence of obesity: results from a prospective cohort study. BMC Public Health 6:258. doi:10.1186/1471-2458-6-258
19. Migueles JH, Cadenas-Sanchez C, Ekelund U, Delisle Nystrom C, Mora-Gonzalez J, Lof M, Labayen I, Ruiz JR, Ortega FB (2017) Accelerometer data collection and processing criteria to assess physical activity and other outcomes: a systematic review and practical considerations. Sports Med 47 (9):1821-1845. doi:10.1007/s40279-017-0716-0
20. Troiano RP, McClain JJ, Brychta RJ, Chen KY (2014) Evolution of accelerometer methods for physical activity research. Br J Sports Med 48 (13):1019-1023. doi:10.1136/bjsports-2014-093546
21. Andersen LB, Harro M, Sardinha LB, Froberg K, Ekelund U, Brage S, Anderssen SA (2006) Physical activity and clustered cardiovascular risk in children: a cross-sectional study (The European Youth Heart Study). Lancet 368 (9532):299-304. doi:10.1016/S0140-6736(06)69075-2
22. Godfrey A, Conway R, Meagher D, G OL (2008) Direct measurement of human movement by accelerometry. Med Eng Phys 30 (10):1364-1386. doi:10.1016/j.medengphy.2008.09.005
23. Santos-Rocha R, Veloso A, Machado ML (2009) Analysis of ground reaction forces in step exercise depending on step pattern and stepping rate. J Strength Cond Res 23 (1):209-224
24. Medved V (2000) Measurement of human locomotion. CRC Press, London
25. Neugebauer JM, LaFiandra M (2018) Predicting ground reaction force from a hip-borne accelerometer during load carriage. Med Sci Sports Exerc 50 (11):2369-2374. doi:10.1249/MSS.0000000000001686
26. Neugebauer JM, Hawkins DA, Beckett L (2012) Estimating youth locomotion ground reaction forces using an accelerometer-based activity monitor. PLoS One 7 (10):e48182. doi:10.1371/journal.pone.0048182
27. Neugebauer JM, Collins KH, Hawkins DA (2014) Ground reaction force estimates from ActiGraph GT3X+ hip accelerations. PLoS One 9 (6):e99023. doi:10.1371/journal.pone.0099023
28. Fortune E, Morrow MMB, Kaufman KR (2014) Assessment of gait kinetics using triaxial accelerometers. J Appl Biomech 30 (5):668-674. doi:10.1123/jab.2014-0037
29. Collaboration NRF (2017) Worldwide trends in body-mass index, underweight, overweight, and obesity from 1975 to 2016: a pooled analysis of 2416 population-based measurement studies in 128·9 million children, adolescents, and adults. Lancet 390 (10113):2627-2642. doi:10.1016/s0140-6736(17)32129-3
30. Viester L, Verhagen EA, Oude Hengel KM, Koppes LL, van der Beek AJ, Bongers PM (2013) The relation between body mass index and musculoskeletal symptoms in the working population. BMC Musculoskelet Disord 14:238. doi:10.1186/1471-2474-14-238
31. Veras L (2019) verasls/walking_GRF_ACC: Prediction of walking ground reaction forces based on accelerometry (Version v2.0.0). Zenodo. doi:10.5281/zenodo.3341764
32. Field A, Miles J, Field Z (2012) Discovering statistics using R. 1st edn. Sage, London
33. Staudenmayer J, Zhu W, Catellier DJ (2012) Statistical considerations in the analysis of accelerometry-based activity monitor data. Med Sci Sports Exerc 44 (1 Suppl 1):S61-67. doi:10.1249/MSS.0b013e3182399e0f

34. Bland JM, Altman DG (1986) Statistical methods for assessing agreement between two methods of clinical measurement. Lancet 1 (8476):301-310
35. Giavarina D (2015) Understanding Bland Altman analysis. Biochem Med (Zagreb) 25 (2):141-151. doi:10.11613/BM.2015.015
36. Ancillao A, Tedesco S, Barton J, O'Flynn B (2018) Indirect Measurement of Ground Reaction Forces and Moments by Means of Wearable Inertial Sensors: A Systematic Review. Sensors (Basel) 18 (8). doi:10.3390/s18082564
37. Janz KF, Rao S, Baumann HJ, Schultz JL (2003) Measuring children's vertical ground reaction forces with accelerometry during walking, running and jumping: the Iowa Bone Development Study. Pediatr Exerc Sci 15:34-43
38. Simons C, Bradshaw EJ (2016) Do accelerometers mounted on the back provide a good estimate of impact loads in jumping and landing tasks? Sports Biomech 15 (1):76-88. doi:10.1080/14763141.2015.1123765
39. Welk GJ (2005) Principles of design and analyses for the calibration of accelerometry-based activity monitors. Med Sci Sports Exerc 37 (Supplement):S501-S511. doi:10.1249/01.mss.0000185660.38335.de
40. Wundersitz DW, Gastin PB, Robertson S, Davey PC, Netto KJ (2015) Validation of a trunk-mounted accelerometer to measure peak impacts during team sport movements. Int J Sports Med 36 (9):742-746. doi:10.1055/s-0035-1547265
41. Stiles VH, Metcalf BS, Knapp KM, Rowlands A (2017) A small amount of precisely measured high-intensity habitual physical activity predicts bone heath in pre- and post-menopausal women in UK Biobank. Int J Epidemiol 46 (6):1847-1856. doi:0.1093/ije/dyx080
42. Zifchock RA, Davis I, Hamill J (2006) Kinetic asymmetry in female runners with and without retrospective tibial stress fractures. J Biomech 39 (15):2792-2797. doi:10.1016/j.jbiomech.2005.10.003
43. Vainionpää A, Korpelainen R, Vihriälä E, Rinta-Paavola A, Leppäluoto J, Jämsä T (2006) Intensity of exercise is associated with bone density change in premenopausal women. Osteoporos Int 17 (3):455-463. doi:10.1007/s00198-005-0005-x
44. Kluitenberg B, Bredeweg SW, Zijlstra S, Zahner W, Buist I (2012) Comparison of vertical ground reaction forces during overground and treadmill running. A validation study. BMC Musculoskeletal Disorders 13 (1):1-8
45. Ngoh KJ, Gouwanda D, Gopalai AA, Chong YZ (2018) Estimation of vertical ground reaction force during running using neural network model and uniaxial accelerometer. J Biomech. doi:10.1016/j.jbiomech.2018.06.006

**Figure legends**

**Figure 1** Scatterplot of actual pRGRF versus pRACC (left panel, A) and actual pVGRF versus pVACC (right panel, B) from ankle, lower back and hip accelerometer placements. Data points of participants in different BMI categories are highlighted by markers with different colors and shapes. Linear trends for each BMI class are also depicted.

Abbreviations: pRACC, peak resultant acceleration; pRGRF, peak resultant ground reaction force; pVACC, peak vertical acceleration; pVGRF, peak vertical ground reaction force.

**Figure 2** Bland-Altman plots of actual and predicted pRGRF (left panel, A) and pVGRF (right panel, B) from ankle, lower back and hip accelerometer placements derived equations. Continuous thick lines show bias (average of the differences between real and predicted pGRF) while dotted lines show upper and lower limits of agreement (± 2SD). Data points of participants in different BMI categories are highlighted by markers with different colors and shapes.

Abbreviations: pRGRF, peak resultant ground reaction force; pVGRF, peak vertical ground reaction force

**Figure 3** Data represents the relationship between actual (measured by FP) and predicted by the regression equations developed from ankle, lower back and hip-worn accelerometers pGRF in the resultant (left panel, A) and its vertical component (right panel, B). For each speed, none of the predicted pGRF was significantly different ($p>0.05$) from the actual pGRF meadured (exact p value presented above each speed). Moreover, actual and predicted pRGRF and pVGRF significantly increased ($p<0.001$) along with speed increments. Actual and predicted pGRF values were systematically shifted in each speed (x axis) to avoid overlapping and facilitate result interpretation/visualization. Data are presented as mean ± confidence interval. Abbreviations: pRGRF, peak resultant ground reaction force; pVGRF, peak vertical ground reaction force.

**Figure 4** Bland-Altman plots of actual and predicted pVGRF by our equation (left panel, A) and by Neugebauer's equation [27] (right panel, B) from hip derived accelerometer data. Continuous thick lines show bias (average of the differences between real and predicted pGRF) while dotted lines show upper and lower limits of agreement (± 2SD).

Abbreviations: pVGRF, peak vertical ground reaction force.

**Table 1** Regression equations, $R^2$ and accuracy indices.

| Accelerometer placement | Regression equations | $R^2$ | MAE | MAPE | RMSE |
|---|---|---|---|---|---|
| Ankle | pRGRF (N) = 188.5506 - 2.0401(pRACC) - 6.9732($pRACC^2$) + 6.5685(body mass) + 1.8811(pRACC * body mass) | 0.93 | 69.4 | 6.3% | 91.4 |
| | pVGRF (N) = 173.0649 + 17.9895(pVACC) - 24.8697($pVACC^2$) + 5.3546(body mass) + 3.1920(pVACC * body mass) | 0.92 | 72.9 | 6.7% | 98.2 |
| Lower Back | pRGRF (N) = - 698.7031 + 1047.5129(pRACC) - 345.2605($pRACC^2$) + 3.8294(body mass) + 6.0219(pRACC * body mass) | 0.94 | 62.1 | 5.5% | 81.5 |
| | pVGRF (N) = - 776.8934 + 1042.9052(pVACC) - 336.2115($pVACC^2$) + 6.2132(body mass) + 5.0805(pVACC * body mass) | 0.89 | 76.3 | 6.6% | 104.1 |
| Hip | pRGRF (N) = - 300.9909 + 522.6850(pRACC) - 171.5606($pRACC^2$) + 3.9596(body mass) + 5.3671(pRACC * body mass) | 0.95 | 57.4 | 5.4% | 74.1 |
| | pVGRF (N) = - 435.7365 + 586.6627(pVACC) - 188.9689($pVACC^2$) + 5.8047(body mass) + 4.9544(pVACC * body mass) | 0.93 | 62.5 | 5.7% | 86.3 |

Abbreviations: MAE, mean absolute error; MAPE, mean absolute percent error; pRACC, peak resultant acceleration; pRGRF, peak resultant ground reaction force; pVACC, peak vertical acceleration; pVGRF, peak vertical ground reaction force; RMSE, root mean square error.

**Table 2** Accuracy indices of ours and Neugebauer equation to predict pVGRF with data from accelerometers placed at hip

| Sample | Our equation | | | Neugebauer equation | | |
|---|---|---|---|---|---|---|
| | MAE | MAPE | RMSE | MAE | MAPE | RMSE |
| Normal weight and overweight | 58.5 | 6.4% | 76.7 | 173.0 | 18.0% | 187.5 |
| Class I to III obesity | 67.3 | 4.7% | 96.6 | 175.7 | 12.6% | 197.7 |
| Whole sample | 62.5 | 5.7% | 86.3 | 174.3 | 15.6% | 192.2 |

Abbreviations: MAE, mean absolute error; MAPE, mean absolute percent error; pVGRF, peak vertical ground reaction force; RMSE, root mean square error.

Figure 1

Click here to access/download;Figure;Figure_1.tiff

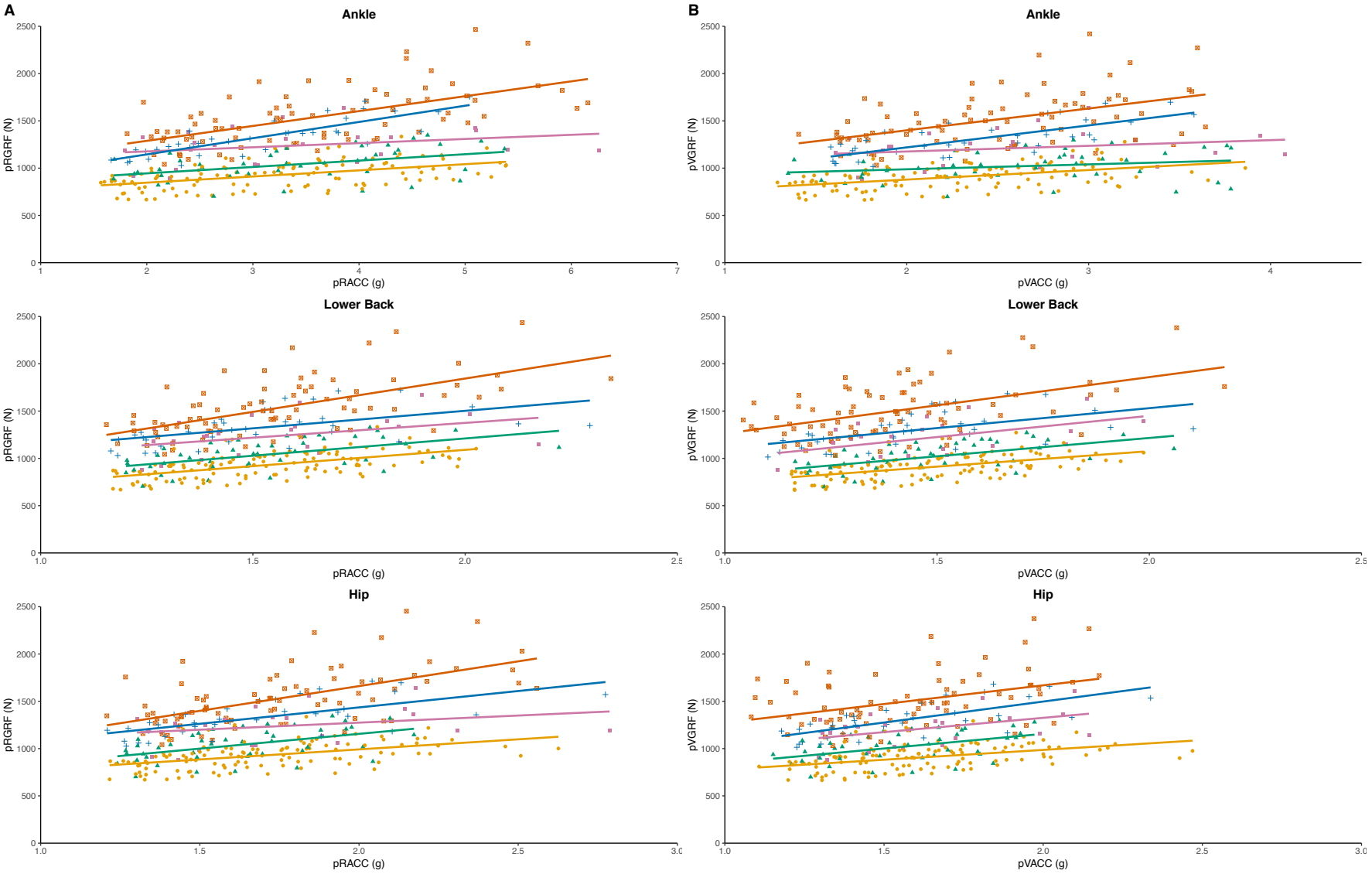

Figure 2



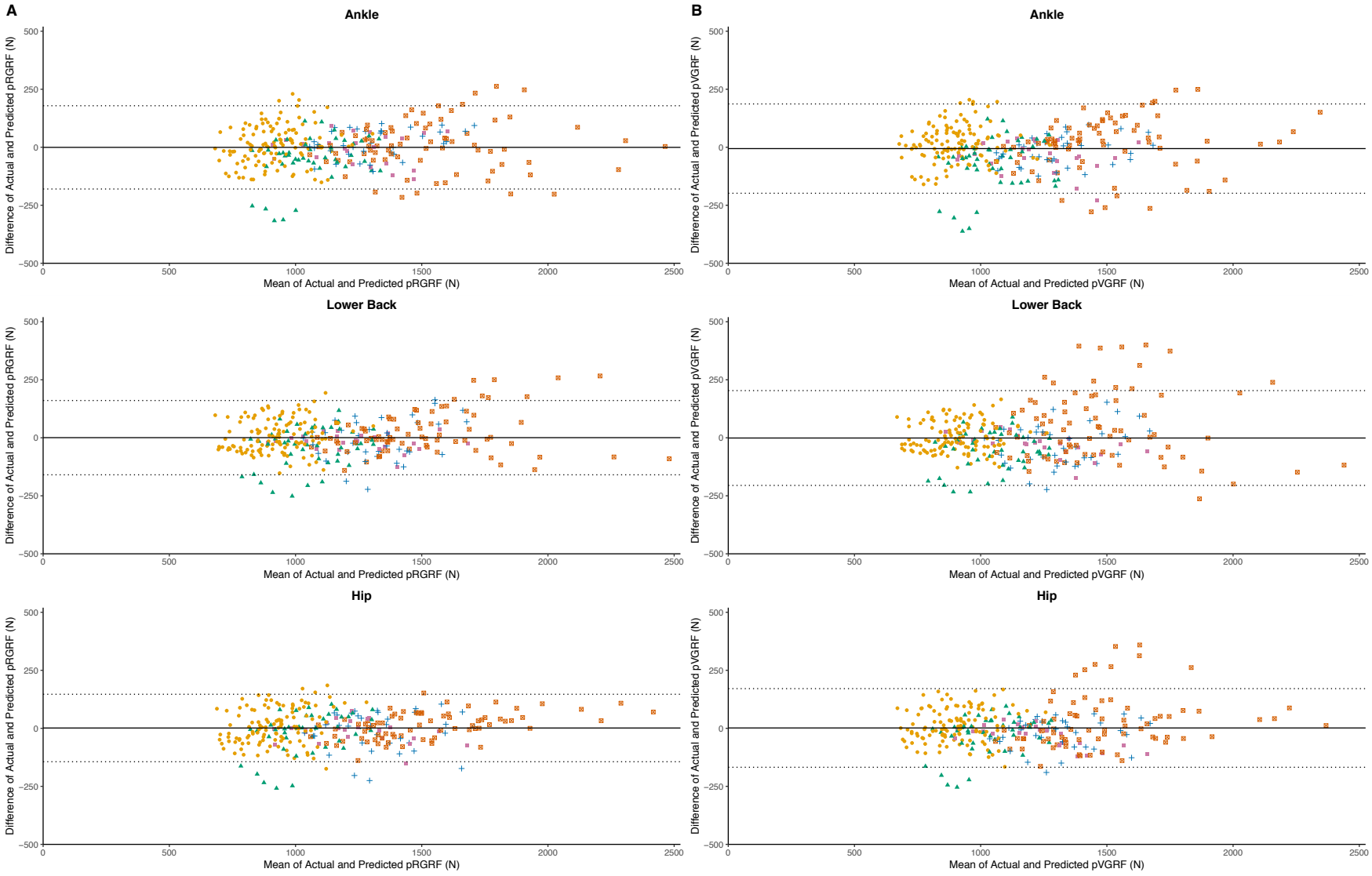

Figure 3

Click here to access/download;Figure;Figure_3.tiff

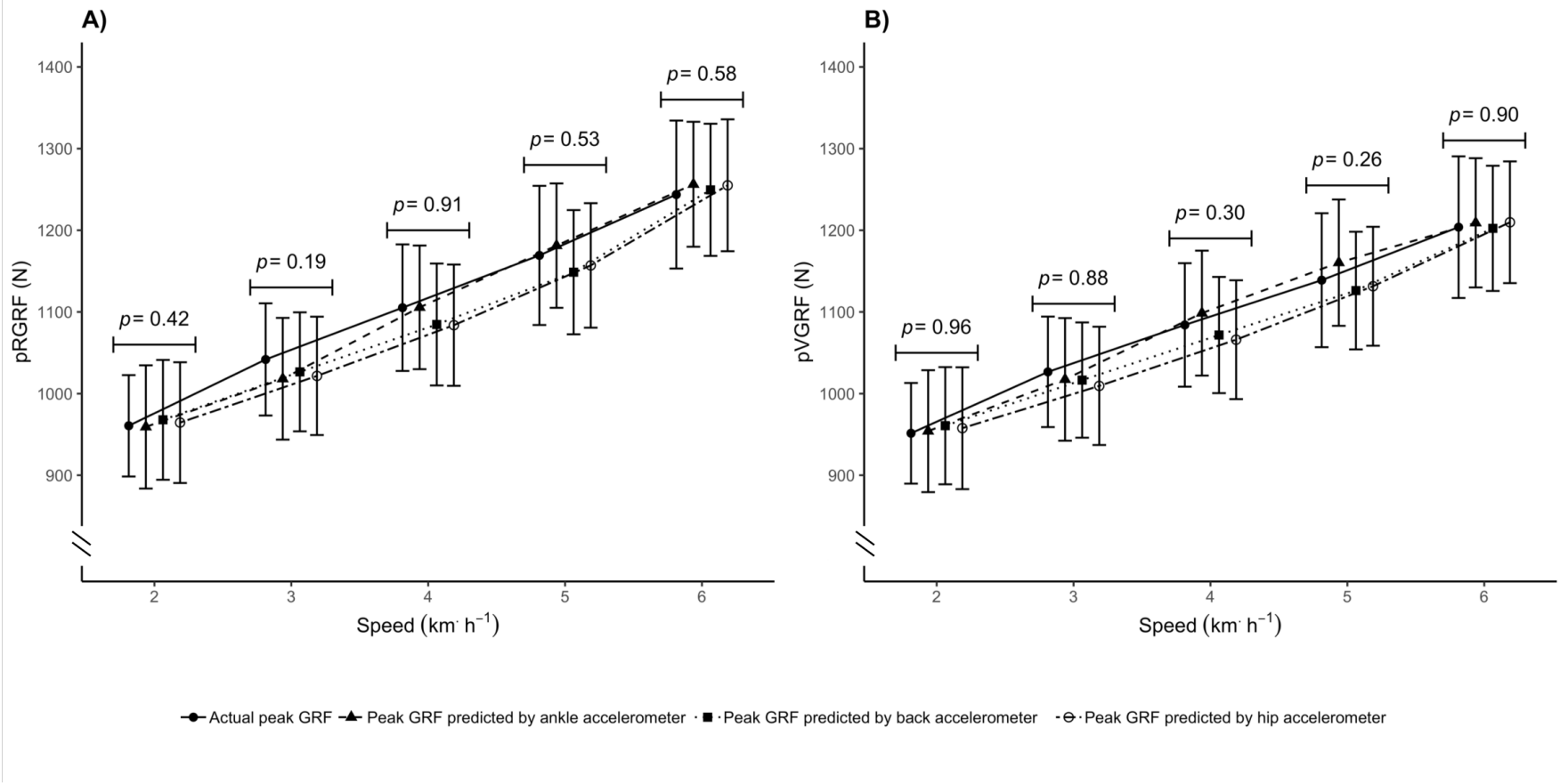

Figure 4