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Accurate estimation of peak vertical ground reaction force using the duty factor in level treadmill running

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This study aimed to (1) construct a statistical model (SMM) based on the duty factor (DF) to estimate the peak vertical ground reaction force ($F_{v,\max}$) and (2) to compare the estimated $F_{v,\max}$ to force plate gold standard (GSM). One hundred and fifteen runners ran at 9, 11, and 13 km/h. Force (1000 Hz) and kinematic (200 Hz) data were acquired with an instrumented treadmill and an optoelectronic system, respectively, to assess force-plate and kinematic based DFs. SMM linearly relates $F_{v,\max}$ to the inverse of DF because DF was analytically associated with the inverse of the average vertical force during ground contact time and the latter was *very highly* correlated to $F_{v,\max}$. No systematic bias and a 4% root mean square error (RMSE) were reported between GSM and SMM using force-plate based DF values when considering all running speeds together. Using kinematic based DF values, SMM reported a systematic but small bias (0.05BW) and a 5% RMSE when considering all running speeds together. These findings support the use of SMM to estimate $F_{v,\max}$ during level treadmill runs at endurance speeds if underlying DF values are accurately measured.

KEYWORDS
biomechanics, curve fitting, gait analysis, linear regression, statistical model

1 | INTRODUCTION

Running offers many health benefits. However, between 19% and 79% of recreational runners are expected to contract a running related injury each year.[1,2] Therefore, the incidence of these injuries is high. The magnitude of the peak of the vertical ground reaction force ($F_{v,\max}$; active peak force)[3,4] is related to an increased risk for various running musculoskeletal injuries.[5–7] In addition, the peak axial tibial compressive force was shown to be moderately correlated with $F_{v,\max}$.[8] Hence, Sasimontonkul et al.[4] suggest that the risk of tibial stress fracture is most closely associated with the forces acting during midstance, and that adopting a running technique to reduce $F_{v,\max}$ may reduce the risk of tibial stress fracture. These observations make $F_{v,\max}$ to be a biomechanical variable of major interest that needs to be accurately measured.

To measure $F_{v,\max}$, the gold standard method (GSM) is to use a force plate, which could unfortunately not always be affordable or at hand.[9,10] In such case, a first alternative would be to use a sacral-mounted inertial measurement unit (IMU),[11–13] which is low-cost and practical to use in a coaching environment.[14] For instance, Alcantara et al.[12] predicted $F_{v,\max}$ using machine learning and reported a root mean square error (RMSE) of 0.15 body weight (BW). Moreover, weak to moderate correlations were obtained between $F_{v,\max}$ measured using GSM and estimated using IMU data.[11] These authors observed an effect of the low-pass cutoff frequency used for the IMU data, where a better correlation was depicted for a 10 Hz than a 5 or 30 Hz cutoff frequency. A second alternative would be to assume a sine-wave model for the vertical ground reaction force.[15–17] Doing so, $F_{v,\max}$ (expressed in BW units) could be estimated based on contact (t_c) and flight (t_f) times.[17] This method reported a 7% bias compared to GSM for treadmill running.[17] A third alternative would be to construct a statistical model relating $F_{v,\max}$ to the duty factor (DF),[18,19] that is, the ratio of t_c to stride duration (Equation 3). Ultimately, this model (statistical model method: SMM) could estimate $F_{v,\max}$ only using a temporal parameter, that is, DF. Such SMM model would prove to be useful if the measurement system provides an accurate estimation of DF (or t_c and t_f, that is, its subcomponents) but does not provide an estimation of $F_{v,\max}$, as it is often the case for foot-worn[20] or ankle-worn[21] inertial sensors. However, SMM has, to the best of our knowledge, never been constructed so far.

Hence, the first purpose of this study was to construct a statistical model relating $F_{v,\max}$ to DF, where both variables were obtained from force plate data, and to compare $F_{v,\max}$ estimated by this model to GSM. Then, as a practical application, the second purpose of this study was to use SMM with kinematic based DF values to estimate $F_{v,\max}$ and to compare these estimations to GSM. We hypothesized that (1) $F_{v,\max}$ estimated by SMM using force-plate based DF values should report a similar RMSE than in Alcantara et al.,[12] that is, ~0.15BW and (2) $F_{v,\max}$ estimated by SMM using kinematic based DF values should also report an RMSE of ~0.15BW.

2 | MATERIALS AND METHODS

2.1 | Participant characteristics

An existing database of 115 recreational runners, 87 males (age: 30 ± 8 years, height: 180 ± 6 cm, body mass: 70 ± 7 kg, and weekly running distance: 38 ± 24 km) and 28 females (age: 30 ± 7 years, height: 169 ± 5 cm, body mass: 61 ± 6 kg, and weekly running distance: 22 ± 16 km), was used in the present study.[22] For study inclusion, participants were required to not have current or recent lower-extremity injury (≤1 month), to run at least once a week, and to have an estimated maximal aerobic speed ≥14 km/h. The study protocol was approved by the local Ethics Committee (CER-VD 2020-00334).

2.2 | Statistical model method

First, in what follows, DF is shown to be analytically proportional to the inverse of the mean vertical ground reaction force during t_c ($F_{v,\mathrm{mean}}$), that is, the integral of the vertical ground reaction force during t_c divided by t_c ($F_{v,\mathrm{mean}} = \int_{\mathrm{FS}}^{\mathrm{TO}} F_v(t)\mathrm{d}t \,/\, t_c$, where FS, TO, and $F_v(t)$ represent foot-strike, toe-off, and vertical ground reaction force signal, respectively). Starting from vertical momentum conservation law during a running step, which states that the vertical momentum at FS is the same than the one at contralateral FS, or, in other words, that the integral of the vertical external forces during a running step is null, one can easily obtain that:

$$\int_{\mathrm{FS}}^{\mathrm{TO}} \left(F_v(t) - \mathrm{mg}\right)\mathrm{d}t - \mathrm{mg}t_f = 0 \tag{1}$$

where mg represents BW. Solving Equation 1 for t_f leads to

$$t_f = \frac{\int_{\mathrm{FS}}^{\mathrm{TO}} F_v(t)\mathrm{d}t}{\mathrm{mg}} - t_c = t_c\frac{F_{v,\mathrm{mean}}}{\mathrm{mg}} - t_c \tag{2}$$

where the definition of $F_{v,\mathrm{mean}}$ was used in the last step. Ultimately, by expressing DF as (the stride duration is assumed to be equal to two times $t_c + t_f$):

$$\mathrm{DF} = \frac{t_c}{2\left(t_c + t_f\right)} \tag{3}$$

one can get that:

$$\mathrm{DF} = \frac{\mathrm{mg}}{2\,F_{v,\,\mathrm{mean}}} \tag{4}$$

which proves that when DF is computed using Equation 3, DF is analytically proportional to the inverse of $F_{v,\mathrm{mean}}$.

Then, assuming that $F_{v,\mathrm{mean}}$ is linearly related to $F_{v,\max}$ (linearity assumption), as it is analytically the case when using a sine-wave model for the vertical ground reaction force,[17] DF should be linearly related to the inverse of $F_{v,\max}$. Therefore, rearranging for $F_{v,\max}$ should lead to a statistical model relating $F_{v,\max}$ to DF (see Equation 5 in the Results section), for which the accuracy should depend on the validity of the linearity assumption.

SMM could then be used to estimate $F_{v,\max}$ but using DF values obtained from any measurement systems (IMU, motion capture system, light-based optical technology, etc.), which is a direct practical application of SMM.

Indeed, using SMM with force-plate based DF values to estimate $F_{v,\max}$ does not prove to be useful because, in this case, a force-plate based $F_{v,\max}$ (gold standard) is directly provided, but this was required to construct SMM. However, using SMM with DF values obtained, for instance, from a motion capture system (kinematic data) allows estimating $F_{v,\max}$ when no force plate is available.

2.3 | Experimental procedure, data collection, and data processing

The experimental procedure, data collection, and data processing have been described in more detail elsewhere.[22] Briefly, after providing written informed consent, 43 retroreflective markers of 12.5 mm diameter were affixed to skin and shoes of individuals over anatomical landmarks using double-sided tape following standard guidelines.[23] Then, a 7-min warm-up run (9–13 km/h) was performed on an instrumented treadmill (Arsalis T150 – FMT-MED). This was followed, after a short break (<5 min), by a 1-s static trial on the same treadmill for calibration. Then, four retroreflective markers were removed (medial epicondyle of femur and apex of medial malleolus), and three 1-min runs (9, 11, and 13 km/h) were performed in a randomized order (1-min recovery between each run). Three-dimensional (3D) kinematic and kinetic data were collected during the last 30 s following the 30-s mark of running trials (40 ± 9 running steps), resulting in at least 25 steps being analyzed.[24] All participants wore their habitual running shoes and were familiar with running on a treadmill as part of their usual training program.

Motion capture (eight cameras, Vicon) and Vicon Nexus software v2.9.3 (Vicon) were used to collect whole-body 3D kinematic data at 200 Hz. The force plate embedded into the treadmill was used to collect synchronized kinetic data (1000 Hz). 3D marker and ground reaction force (analog signal) were exported in .c3d format and processed in Visual3D Professional software v6.01.12 (C-Motion Inc.). Ground reaction force data were down sampled to 200 Hz to match the sampling frequency of marker data. Then, 3D marker and ground reaction force data were low-pass filtered at 20 Hz using a fourth-order Butterworth filter.[25]

2.4 | Biomechanical variables obtained from force plate data

For each running trial, force-plate based t_c and t_f were obtained from FS and TO events identified using the vertical ground reaction force and implemented within Visual3D. These events were detected by applying a 20 N threshold to the vertical component of the ground reaction force.[26] t_c was defined as the time from FS to TO of the same foot while t_f was given by the time from TO of one foot to FS of the contralateral foot. Then, force-plate based DF was given by Equation 3.

Force-place based $F_{v,\max}$ and $F_{v,\text{mean}}$ were given by the maximum vertical ground reaction force between FS and TO events and by the integral of the vertical ground reaction force between FS and TO events divided by t_c. The integration was carried out numerically using a second-order method known as trapezoidal rule. $F_{v,\max}$ and $F_{v,\text{mean}}$ were expressed in BW while DF was given in percent.

2.5 | Biomechanical variables obtained from kinematic data

t_c, t_f, and DF were calculated from FS and TO events identified using kinematic data. The kinematic algorithm which permitted to obtain FS and TO events has been implemented within Visual3D and was based only on the foot markers. This algorithm has been described elsewhere and reported systematic biases and root mean square errors (RMSE) ≤12 ms compared to gold standard events at running speeds ranging from 9 to 13 km/h.[27] The kinematic based DF could then be inserted into SMM to estimate $F_{v,\max}$ when no force plate is available. Systematic biases of 6 ms, −6 ms, and 0.9% were reported for t_c, t_f, and DF when considering all running speeds together (see Section S1 of Appendix S1).

All force-plate and kinematic based biomechanical variables extracted from the 10 analyzed strides were averaged for each participant for subsequent analyses.

2.6 | Data analysis

The error of SMM based on both force plate and kinematic based DF to estimate $F_{v,\max}$ was calculated using RMSE (in absolute and relative units, that is, normalized by the corresponding mean value over all participants and obtained using GSM) considering each running speed separately and all running speeds together. Data analysis was performed using Python (v3.7.4, http://www.python.org).

2.7 | Statistical analysis

All data are presented as mean ± standard deviation. Since all data were normally distributed based on Kolmogorov–Smirnov tests ($p \geq 0.13$), Pearson correlation coefficients (r) between DF and $F_{v,\text{mean}}^{-1}$, $F_{v,\text{mean}}$ and $F_{v,\max}$, and $F_{v,\max}^{-1}$ and DF as well as corresponding p-values were extracted considering each running speed separately and all running speeds together. Correlations were considered *very high*, *high*, *moderate*, *low*, and *negligible* when absolute r values were between 0.90–1.00, 0.70–0.89, 0.50–0.69, 0.30–0.49, and 0.00–0.29, respectively.[28] Coefficient of determination (R^2) was given by the square of r.

Bland–Altman plots were constructed to examine the presence of systematic bias on $F_{v,\max}$ between GSM and SMM.[29] Corresponding lower and upper limit of agreements and 95% confidence intervals (CI) were calculated. Systematic biases have a direction, that is, positive values indicate overestimations of SMM while negative values indicate underestimations. Then, after having inspected residual plots and having observed no obvious deviations from homoscedasticity or normality, Student's t-tests were used to compare GSM and SMM. Differences between GSM and SMM were quantified using Cohen's d effect size and interpreted as *very small*, *small*, *moderate*, and *large* when $|d|$ values were close to 0.01, 0.2, 0.5, and 0.8, respectively.[30] The analyses comparing SMM to GSM were performed considering each running speed separately and all running speeds together and two times (1) using force-plate based and (2) using kinematic based DF values. Statistical analysis was performed using Jamovi (v1.6, https://www.jamovi.org) with a level of significance set at $p \leq 0.05$.

3 | RESULTS

Considering all running speeds together, DF was *very highly* correlated to $F^{-1}_{v,\text{mean}}$ ($r = 1.00$, $p < 0.001$, Figure 1A), $F_{v,\text{mean}}$ was *very highly* correlated to $F_{v,\max}$ ($r = 0.90$, $p < 0.001$, Figure 1B), and $F^{-1}_{v,\max}$ was *very highly* correlated to DF ($r = 0.91$, $p < 0.001$, Figure 1C), which led to the following SMM (obtained using a linear least-squares regression; Equation 5):

$$F_{v,\max} = \frac{1}{0.0097\,\text{DF} + 0.0635} \tag{5}$$

Considering each running speed separately, DF was *very highly* correlated to $F^{-1}_{v,\text{mean}}$ ($r = 1.00$, $p < 0.001$), $F_{v,\text{mean}}$ was *highly* correlated to $F_{v,\max}$ ($r \geq 0.88$, $p < 0.001$), and $F^{-1}_{v,\max}$ was *highly* correlated to DF ($r \geq 0.88$, $p < 0.001$).

Using force-plate based DF to estimate $F_{v,\max}$, RMSEs of 4% and up to *small* effect sizes (Table 1) were reported between GSM and SMM when considering each running speed separately and all running speeds together. No systematic biases were obtained at 11 km/h and when considering all running speeds together while small but systematic biases were reported at 9 and 13 km/h (Figure 2A and Table 1). $F_{v,\max}$ estimated using SMM based on force-plate DF values was significantly different than $F_{v,\max}$ obtained using GSM at 9 and 13 km/h ($P \leq 0.03$; Table 2).

Using kinematic based DF to estimate $F_{v,\max}$, systematic biases were obtained between GSM and SMM at each speed employed (though very small at 13 km/h) as well as when considering all running speeds together (Figure 2B and Table 1). RMSEs were up to 6% and effect sizes up to *moderate* (Table 1) when considering each running speed separately and all running speeds together. $F_{v,\max}$ estimated using SMM based on kinematic DF values was significantly different than $F_{v,\max}$ obtained using GSM at 9 and 11 km/h as well as when considering all running speeds together ($p < 0.001$; Table 2).

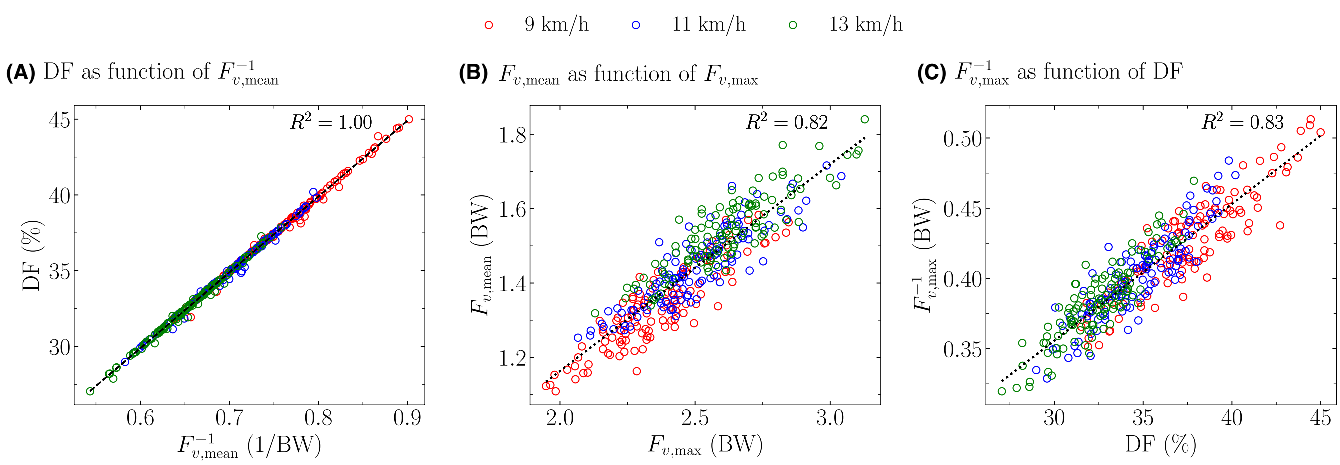

FIGURE 1 Linear relation obtained using Pearson correlation between (A) duty factor (DF) and the inverse of the mean vertical ground reaction force during contact time ($F_{v,\text{mean}}$), (B) $F_{v,\text{mean}}$ and peak vertical ground reaction force ($F_{v,\max}$), and (C) the inverse of $F_{v,\max}$ and DF, together with their corresponding coefficient of determination (R^2), and considering all running speeds together (9, 11, and 13 km/h). Ground reaction force variables were expressed in body weight (BW). Each dot represents the average over the 10 analyzed strides for one subject at a particular running speed.

TABLE 1 Systematic bias, lower limit of agreement (lloa), upper limit of agreement (uloa), root mean square error [RMSE; both in absolute (body weight; BW) and relative (%) units], and Cohen's d effect size between peak vertical ground reaction force ($F_{v,\max}$) obtained using statistical model (SMM) and gold standard (GSM) method, considering each running speed separately (9, 11, and 13 km/h) and all running speeds together.

	Running speed	Systematic bias (BW)	Lloa (BW)	Uloa (BW)	RMSE (BW)	d (−)
GSM vs. force-plate based SMM	9 km/h	−0.03 [−0.04, −0.01]	−0.20 [−0.22, −0.17]	0.14 [0.11, 0.17]	0.09 (4%)	0.15
	11 km/h	0.00 [−0.02, 0.01]	−0.18 [−0.21, −0.15]	0.17 [0.15, 0.20]	0.09 (4%)	0.02
	13 km/h	0.02 [0.00, 0.04]	−0.16 [−0.19, −0.13]	0.20 [0.17, 0.23]	0.09 (4%)	−0.11
	All together	0.00 [−0.01, 0.01]	−0.18 [−0.20, −0.17]	0.18 [0.16, 0.19]	0.09 (4%)	0.02
GSM vs. kinematic based SMM	9 km/h	−0.09 [−0.11, −0.07]	−0.07 [−0.29, −0.33]	0.11 [0.08, 0.15]	0.14 (6%)	0.50
	11 km/h	−0.05 [−0.07, −0.03]	−0.26 [−0.29, −0.23]	0.16 [0.13, 0.19]	0.12 (5%)	0.27
	13 km/h	−0.01 [−0.03, 0.01]	−0.22 [−0.25, −0.18]	0.20 [0.16, 0.23]	0.11 (4%)	0.06
	All together	−0.05 [−0.06, −0.04]	−0.27 [−0.29, −0.25]	0.17 [0.15, 0.19]	0.12 (5%)	0.23

Note: 95% confidence intervals are given in square brackets. SMM based on both force plate and kinematic data were used to estimate $F_{v,\max}$. For systematic bias, positive and negative values indicate that SMM overestimated and underestimated $F_{v,\max}$, respectively.

4 | DISCUSSION

In line with our first and second hypotheses, RMSEs of 0.09 and 0.12BW (4% and 5%) were obtained for SMM based on force plate and kinematic data, respectively. Conventional statistical approaches demonstrated no systematic bias of $F_{v,\max}$ between GSM and SMM based on force plate data when considering all running speeds together while systematic but small bias (−0.05BW) was obtained between GSM and SMM based on kinematic data. These results suggest SMM to be a valid method to estimate $F_{v,\max}$ if underlying DF values are accurately measured.

The linear relation between DF and the inverse of $F_{v,\text{mean}}$, which has been analytically derived (Equation 4) when DF is computed using Equation 3, was confirmed by the *very high* correlation reported in this study ($R^2 = 1.00$; Figure 1A). Nonetheless, several points did not exactly fall on the regression line (Figure 1A). This might be explained by several reasons. First, the integration of the vertical ground reaction force encompasses errors due to its numerical nature (second-order trapezoidal rule). Second, even though the raw vertical ground reaction force signal was filtered (fourth-order Butterworth low-pass filter at 20 Hz), it still contains some noise, thus affecting the outcome of its numerical integration. Third, the calibration of the force plate may be not 100% accurate, thus affecting the values of the force signal. It is also worth mentioning that similar results would have been obtained when using the exact definition of DF, that is, the ratio of t_c over stride time.[18,19] Indeed, RMSE ≤0.12% were obtained when comparing DF calculated using Equation 3 to its exact definition (see Section S2 of Appendix S1). This result corroborates the small symmetry indices ≤4% previously reported for the step time of competitive, recreational, and novice runners at running speeds ranging from 8 to 12 km/h.[31] The authors reported similar symmetry indices for DF (≤4%), the reason being that the stride time was close to perfectly symmetric (≤1%), reflecting that the symmetry of DF was mostly affected by the symmetry of t_c (~3%).[31]

SMM reported no systematic bias and an RMSE of 4% when using force plate DF values and considering all running speeds together (Figure 2A and Tables 1 and 2), which permitted to validate the proposed statistical model (Equation 5). However, using SMM with force-plate based DF values to estimate $F_{v,\max}$ does not prove to be useful because, in this case, a gold standard $F_{v,\max}$ is directly provided. Therefore, as a direct practical application, SMM was used with DF values obtained from kinematic data to estimate $F_{v,\max}$. A systematic bias of −0.05BW and an RMSE of 5% were reported when considering all running speeds together (Figure 2B and Tables 1 and 2). $F_{v,\max}$ estimated using sacral-mounted IMUs reported similar differences[11] [≤20 N (≤0.03BW for a 70 kg person) at 14–19 km/h] and RMSE[12] (0.15BW at 13.5–19.5 km/h) with respect to GSM than SMM used in the present study. In addition, a 6% error on $F_{v,\max}$ (6–21 km/h) was reported using an IMU placed on the leg along the tibial axis[32] while a 3% error (10–14 km/h) was achieved using three IMUs (two on lower legs and one on pelvis) and two artificial neural networks.[33] Thus, estimated $F_{v,\max}$ depicted similar error (~5%) than previous estimations which used IMUs.

$F_{v,\max}$ was estimated using SMM, a statistical model solely based on DF (Equation 5) and reported a 5% RMSE (Table 1). The only requirement to obtain an accurate estimation of $F_{v,\max}$ is that DF, or the two variables defining it, that is, t_c and t_f, should be accurately measured (see Section S1 of Appendix S1). Therefore, SMM could be combined with any measurement system accurately

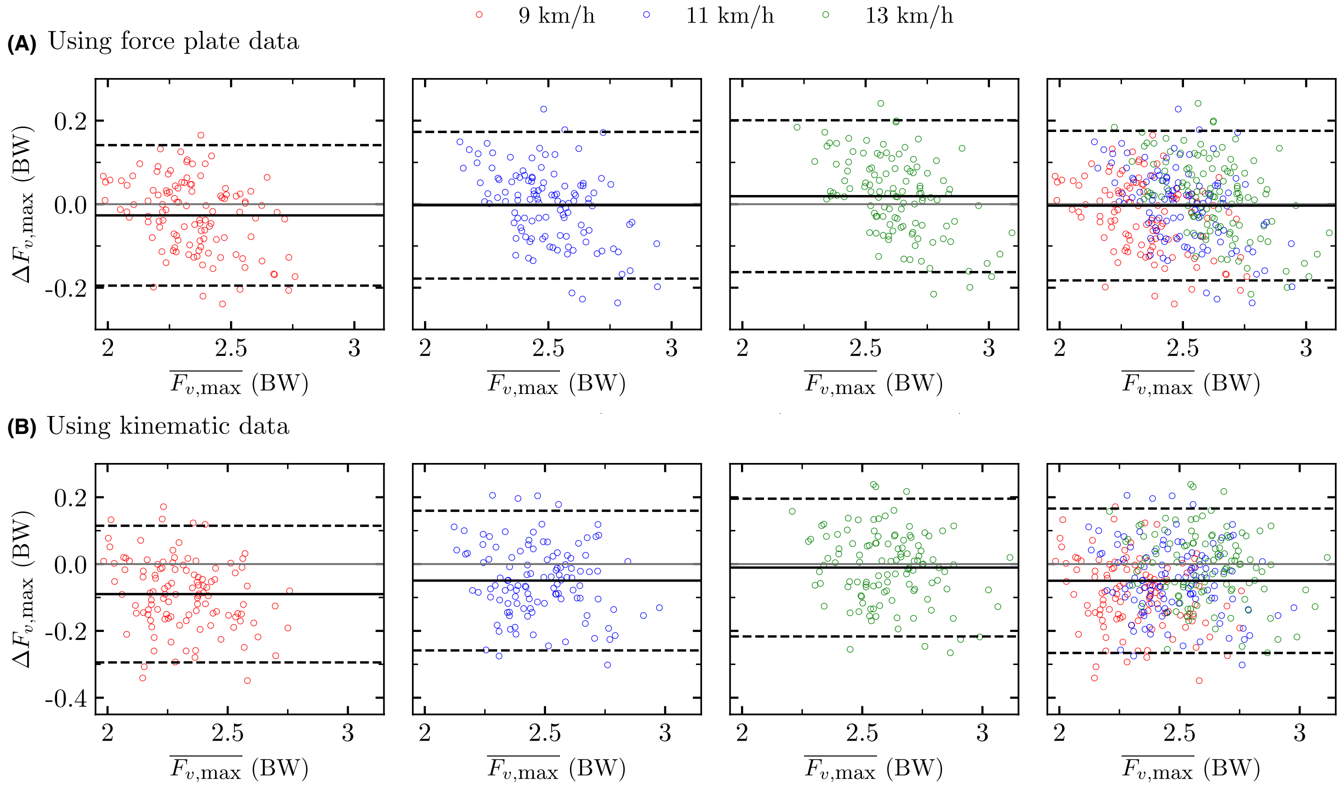

FIGURE 2 Comparison of peak vertical ground reaction force [$F_{v,\max}$; in body weight (BW)] obtained using gold standard method and statistical model method (SMM) [differences (Δ) as function of mean values together with systematic bias (black solid line) as well as lower and upper limit of agreements (black dashed lines), that is, Bland–Altman plots] considering each running speed separately (9, 11, and 13 km/h) and all running speeds together. The estimation of $F_{v,\max}$ using SMM was based on (A) force plate data and (B) kinematic data. Positive and negative Δ values indicate an overestimation and underestimation of $F_{v,\max}$ by SMM. Each dot represents the average over the 10 analyzed strides for one subject at a particular running speed.

TABLE 2 Peak vertical ground reaction force [$F_{v,\max}$; in body weight (BW)] obtained using gold standard (GSM) and statistical model (SMM) methods, considering each running speed separately (9, 11, and 13 km/h) and all running speeds together.

Running speed	9 km/h	11 km/h	13 km/h	All together
$F_{v,\max}$ using GSM	2.36 ± 0.19	2.50 ± 0.19	2.61 ± 0.19	2.49 ± 0.22
$F_{v,\max}$ using force-plate based SMM	2.34 ± 0.16	2.50 ± 0.15	2.63 ± 0.15	2.49 ± 0.20
p	**0.001**	0.76	**0.03**	0.49
$F_{v,\max}$ using kinematic based SMM	2.27 ± 0.17	2.45 ± 0.17	2.60 ± 0.17	2.44 ± 0.22
p	**<0.001**	**<0.001**	0.29	**<0.001**

Note: SMM based on both force plate and kinematic data were used to estimate $F_{v,\max}$. Significant differences ($p \leq 0.05$) between $F_{v,\max}$ obtained using GSM and SMM as determined by Student's *t*-tests are depicted in bold.

providing DF or its underlying variables, such as an IMU,[11,12] a motion capture system,[27,34,35] or a light-based optical technology.[36] Day et al.[11] reported that a 5 Hz low-pass filtering of the vertical acceleration recorded using a sacral-mounted IMU was resulting in the best correlation between t_c obtained from GSM and their method while a 10 Hz low-pass filter produced the best estimated $F_{v,\max}$. These results demonstrated that different cutoff frequencies were required for different biomechanical parameters, agreeing with previous observations that the low-pass cutoff frequency affected biomechanical outcomes.[37,38] However, using two different filters is not very practical. In this case, SMM could be advantageous as it could avoid using the second filter, which is computationally more expensive than using SMM, without losing accuracy. Indeed, SMM could be applied using estimated t_c and t_f from the IMU to directly obtain $F_{v,\max}$.

A few limitations to this study exist. SMM was constructed using running trials between 9 and 13 km/h and using treadmill runs. Therefore, this study could not conclude that SMM would correctly estimate $F_{v,\max}$ at faster running speeds and overground. Hence, further studies should record running trials at faster running speeds and overground to obtain the accuracy of SMM in these conditions. However, although controversial,[39] SMM might perform well overground, at least at similar running speeds than the ones used to construct the statistical model (9–13 km/h), because spatiotemporal parameters between treadmill and overground running are largely comparable.[40] Moreover, SMM tries to estimate $F_{v,\max}$ as if it was obtained using the vertical ground reaction force signal recorded by the specific instrumented treadmill used in the present study. Though the choice of filter and frequency used to filter the vertical ground reaction force (20 Hz and fourth-order Butterworth filter herein) should be chosen to remove as much noise as possible without altering the force signal, that is, everyone should have a similar force signal independently of the underlying force plate, there might still be small discrepancies in the force signals recorded by different instrumented treadmills. Hence, using another instrumented treadmill might affect the integration of the vertical ground reaction force signal and the determination of FS and TO events, and thus the coefficients of the statistical model (Equation 5). Therefore, further studies investigating if the choice of the other instrumented treadmill affects the coefficients of the statistical model are needed and would allow generalizing to a statistical model that estimates $F_{v,\max}$ independently of the instrumented treadmill employed.

4.1 | Perspective

A simple statistical model solely based on DF was constructed to estimate $F_{v,\max}$ (Equation 5). This model was shown to provide an accurate estimation of $F_{v,\max}$ if underlying DF values or its subcomponents (t_c and t_f; Equation 3) are accurately measured. Hence, this model could be implemented in any measurement system that accurately provides DF values (e.g., a smartwatch and/or smartphone). This would allow to monitor $F_{v,\max}$ and loading in real time and could therefore help for preventing running related injuries.

5 | CONCLUSION

To conclude, this study proposed to construct a statistical model only using the DF to estimate $F_{v,\max}$, because DF is analytically related to $F_{v,\text{mean}}$ and the latter is *very highly* correlated to $F_{v,\max}$. Considering all running speeds together and using force-plate based DF values for SMM, no systematic bias and a 4% RMSE were reported between GSM and SMM. Using kinematic based DF values, SMM reported a systematic but small bias (−0.05BW) and a 5% RMSE when considering all running speeds together. Therefore, the findings of this study support the use of SMM to estimate $F_{v,\max}$ during level treadmill runs at endurance speeds if underlying DF values are accurately measured.

AUTHOR CONTRIBUTIONS

Conceptualization, A.P., T.L., C.G., and D.M.; methodology, A.P., T.L., C.G., and D.M.; investigation, A.P., T.L., and B.B.; formal analysis, A.P. and B.B.; writing—original draft preparation, A.P.; writing—review and editing, A.P., T.L., B.B., C.G., and D.M.; supervision, A.P., T.L., C.G., and D.M.

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CONFLICT OF INTEREST

No potential competing interest was reported by the authors.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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