



Article

The Influence of Running Technique Modifications on Vertical Tibial Load Estimates: A Combined Experimental and Machine Learning Approach in the Context of Medial Tibial Stress Syndrome

Taylor Miners ^{1,*} , Jeremy Witchalls ^{1,2} , Jaquelin A. Bousie ^{1,2} , Ceridwen R. Radcliffe ² and Phillip Newman ^{1,2}

¹ Department of Physiotherapy, University of Canberra, Canberra, ACT 2617, Australia; jaquelin.bousie@canberra.edu.au (J.A.B.); phillip.newman@canberra.edu.au (P.N.)

² Research Institute for Sport and Exercise, University of Canberra, Canberra, ACT 2617, Australia; ceridwen.radcliffe@canberra.edu.au

* Correspondence: taylorminers@outlook.com



Academic Editors: Tibor Hortobágyi, Melissa Boswell and Ka-Chun (Joseph) Siu

Received: 4 February 2025

Revised: 25 March 2025

Accepted: 28 March 2025

Published: 2 April 2025

Citation: Miners, T.; Witchalls, J.; Bousie, J.A.; Radcliffe, C.R.; Newman, P. The Influence of Running Technique Modifications on Vertical Tibial Load Estimates: A Combined Experimental and Machine Learning Approach in the Context of Medial Tibial Stress Syndrome. *Biomechanics* **2025**, *5*, 22. <https://doi.org/10.3390/biomechanics5020022>

Copyright: © 2025 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Abstract: Background/Objectives: Currently, there is no strong evidence to support interventions for medial tibial stress syndrome (MTSS), a common running injury associated with tibial loading. Vertical ground reaction force (vGRF) and axial tibial acceleration (TA) are the most common methods of estimating tibial loads, yet clinical recommendations for technique modification to reduce these metrics are not well documented. This study investigated whether changes to speed, cadence, stride length, and foot-strike pattern influence vGRF and TA. Additionally, machine-learning models were evaluated for their ability to estimate vGRF metrics. **Methods:** Sixteen runners completed seven 1 min trials consisting of preferred technique, $\pm 10\%$ speed, $\pm 10\%$ cadence, forefoot, and rearfoot strike. **Results:** A 10% speed reduction decreased peak tibial acceleration (PTA), vertical average loading rate (VALR), vertical instantaneous loading rate (VILR), and vertical impulse by 13%, 10.9%, 9.3%, and 3.2%, respectively. A 10% cadence increase significantly reduced PTA (11.5%), VALR (15.6%), VILR (13.5%), and impulse (3.5%). Forefoot striking produced significantly lower PTA (26.6%), VALR (68.3%), and VILR (68.9%). Habitual forefoot strikers had lower VALR (58.1%) and VILR (47.6%) compared to rearfoot strikers. Machine-learning models predicted all four vGRF metrics with mean average errors of 9.5%, 10%, 10.9%, and 3.4%, respectively. **Conclusions:** This study demonstrates that small-scale modifications to running technique effectively reduce tibial load estimates. Machine-learning models offer an accessible, affordable tool for gait retraining by predicting vGRF metrics without reliance on IMU data. The findings support practical strategies for reducing MTSS risk.

Keywords: musculoskeletal injuries; medial tibial stress syndrome; estimated tibial load; vertical ground reaction force; tibial acceleration; machine-learning analysis; running technique; gait retraining; running injuries

1. Introduction

Running is a common activity associated with many sports and is one of the most popular forms of recreational exercise [1,2]. Although running has numerous health benefits [3,4], it is also associated with high rates of injury. Each year, approximately 50% of runners experience injury, with 25% injured at any given time [5]. The most common

cause of running injury is overuse, with up to 79% of this type occurring at or below the knee [6,7].

Medial tibial stress syndrome (MTSS) is responsible for 60% of all lower-limb overuse injuries, affecting up to 35% of athletes and military personnel [8,9]. MTSS is a stress reaction that occurs in the tibia in response to an increase in load, causing exercise-related diffuse, aching pain in the lower leg [10]. Research indicates that in most cases MTSS presents with cortical bone oedema and microtrauma due to repetitive stress and microcracks in the cortical bone [11]. MTSS can decrease performance, cause chronic pain, and can progress from cortical microtrauma to tibial stress fracture [10].

There is currently no reliable evidence to support treatment modalities for MTSS other than prolonged rest and pain medication. However, this was only effective in early phase, low severity MTSS [8–10,12,13], and full recovery can take up to 18 months [14]. High quality evidence has identified several risk factors for the development of MTSS, including sex, weight, age, bone density, previous injury, and foot structure [12,15]. These risk factors have been aggregated into externally validated models that accurately predict 92% of cases [16]. However, most of these risk factors are non-modifiable, and little is known about optimal loads for rehabilitation, or critical loads for the onset of MTSS.

Tibial load is the most common form of measurement used to assess bone stress risk. As bone stress reaction and microtrauma are the most likely cause of MTSS symptoms, this method of assessment is most appropriate [10,17]. However, direct measurement of tibial load requires surgical insertion of a strain gauge to quantify internal forces [18]. Instead, ground reaction force (GRF) and tibial acceleration (TA) are the most widely documented forms of estimation in the literature [19,20]. Specifically, vertical GRF (vGRF) can be evaluated using peaks, rates, and impulse during the stance phase of running. Prospective and retrospective reports established that runners who sustained tibial stress fractures and other overuse injuries exhibited increased vertical average loading rates (VALR), vertical instantaneous loading rates (VILR), and vertical impact peaks (IP) [6,21]. Other research suggests that load volumes may be more associated with increased bone stress than load peaks [22]. Vertical impulse is an example of a cumulative vGRF metric that has been examined in relation to running-related injuries and running speed with varying findings [23–25]. It is yet to be analysed in relation to other aspects of running technique. Peak axial tibial acceleration (PTA) measured by an inertial measurement unit (IMU) has been shown to correlate with all vGRF metrics, and is a more accessible, cost-saving, and practical method of estimating tibial load [17,26–28]. Prospective and retrospective reports suggest that runners with greater PTA have higher rates of overuse injury and stress fracture [21,29]. Given the value of vGRF metrics and the relative ease of measuring PTA, research has proposed the use of machine-learning models to predict vGRF to assist clinicians in making more informed load decisions. These methods use the more accessible IMU data to predict vGRF metrics with varying success [30–32]. However, currently there are no methods of vGRF prediction that do not require access to laboratory equipment.

Gait retraining has been advocated for the prevention and management of MTSS [12], and generally involves changes to speed, cadence, and foot strike [33,34]. However, the recent research is contrasting [35–37]. Foot-strike patterns are differentiated by the section of the foot that makes initial contact and are each associated with individual loading mechanisms. A forefoot strike has been suggested to reduce exercise-related lower leg pain [35], and has been associated with lower rates of injury [36]. But, a shift to a forefoot/midfoot-strike pattern has shown negligible effects on loading rates [38], and is associated with increases in tibial load estimates and rates of injury dependent on surface incline [37,39]. Most studies use a single form of tibial load estimation and primarily investigate athletic populations. Currently, to the knowledge of the research team, there is no study that

investigates speed, cadence, stride length, and foot strike by analysing multiple tibial load estimates simultaneously, and no method of estimating vGRF metrics without access to IMU devices. The primary aims of this study were (1) to determine whether a 10% increase and decrease in speed causes significant changes to vertical load; (2) whether a 10% increase and decrease in cadence causes significant changes to vertical load; (3) to investigate the relationship between stride length and vertical load and; (4) to determine whether a rearfoot or a forefoot foot-strike pattern produces greater vertical load, and if this is dependent on habitual foot-strike pattern. The secondary aim was to evaluate the accuracy of machine-learning models to estimate IP, VALR, VILR, and vertical impulse, with and without reference to IMU data.

It was hypothesised that a decrease in running speed of 10% would result in reduced vertical load; an increase in cadence of 10% would result in reduced vertical load; decreased stride length would result in reduced vertical load; and a forefoot strike would produce less vertical load than a rearfoot strike.

2. Materials and Methods

2.1. Participants

Ethics approval was obtained from the University of Canberra, Human Research Ethics Committee, for a low-risk project involving humans, on 6 March 2024, Project Number 13393. Participants were volunteers from the student body at the University of Canberra. Runners/athletes were included if over the age of 18 and participating in sports with a component of running (at least 15 min, 2 times a week). Participants were excluded if they had any physical or personal limitations impacting running ability (such as injury, muscle soreness/hesitance to participate with full capabilities) or a lower limb injury in the last three months.

2.2. Data Collection

Participants provided information about the nature and volume of weekly running loads via an online questionnaire prior to testing. Standing height and body mass were measured, and participants provided their 'middle-distance' running tempo speed. This was followed by a short, standardised warmup involving dynamic stretching, concentric muscle contraction, aerobic activity, and treadmill safety familiarisation. The primary researcher increased the speed of the treadmill incrementally until each participant's preferred middle-distance running tempo was obtained, and then manually calculated cadence using the SoundBrenner metronome application (Hong Kong, HK). Experimental speed (km/h) and cadence (spm) were calculated as $\pm 10\%$ of the preferred tempo. Blue Trident IMU accelerometers (Vicon, Oxford Metrics, Oxford, UK) were securely attached bilaterally over the distal anteromedial tibia, three centimetres superior of the medial malleolus by the primary researcher with anatomy experience. IMUs were secured using the ankle band provided with the sensors and wrapped with cotton hand-tearable stretch tape to minimise movement.

All participants completed a 7 min running session on a split belt instrumented treadmill (Treadmetrix, Park City, UT, USA), with two 900×600 mm AMTI (Advanced Mechanical Technology, Inc., Watertown, MA, USA) force plates sampling at 1000 Hz. Running cadence was cued to participants via a Bluetooth speaker transmitting audio from the SoundBrenner phone application, and speed was set using the instrumented treadmill operating system. The first 1 min interval was completed at a self-selected speed and cadence, followed by six 1 min intervals at $\pm 10\%$ speed, $\pm 10\%$ cadence, rearfoot strike, and forefoot-strike patterns, with approximately 30 s in between trials. Order of trials was randomised within each aspect of running technique, and changes to speed and cadence

were made in between trials. For foot-strike conditions, participants were cued to contact the ground with either the heel or the balls of the feet. During all 1 min intervals of running, kinetic data were recorded on one force plate after 30 s for 10 consecutive gait cycles to allow for participants to adjust to the treadmill speed and the set cadence. Video footage was captured for running trials using a Blackfly S BFS-U3-23S3C high-speed video camera (Vicon, Oxford Metrics, Oxford, UK) sampling at 125 Hz and positioned perpendicular to the treadmill for a sagittal plane view to determine foot-strike pattern. Footage was captured and integrated using Vicon Nexus Software (v2.15), and force-plates were zeroed between trials. IMU data were transferred to Nexus via direct USB connection and video data were transferred after each participant.

2.3. Sample Size Calculation

Power calculations were conducted using G*Power 3.1 (Heinrich-Heine-Universität Düsseldorf, Germany) [40] with $\alpha < 0.05$, $\beta = 0.80$. For speed and cadence, expected effect sizes were based on IP, VALR, and VILR from Hunter et al. [41] and Wang et al. [42]. To detect a large effect size using a repeated measures MANOVA for speed and cadence, 12 participants were required. The same number of participants were required to detect a large effect size for foot strike using a mixed between-within subjects ANOVA. A sample size of 31 participants was required to detect an $r = 0.50$ ($r^2 = 0.23$) correlation based on previous literature [37] using a Pearson product-moment correlation.

2.4. Data Processing and Statistical Analysis

Data were processed using Vicon Nexus software. Force plate and IMU data were filtered using a fourth-order, low-pass Butterworth filter with cut-off frequencies of 30 Hz, and 55 Hz, respectively, determined by a residual analysis and visual data inspection [43]. Data were normalised to 101 points between initial contact and toe-off (stance), and between toe-off and the subsequent initial contact (swing). GRF and TA were extracted in this format using a custom Python script within Vicon Nexus. Previous literature suggests that at least eight trials (strides) are necessary for reliable results in running biomechanics [44]. Data from 10 strides were processed for each trial for all participants, resulting in a total of 1120 strides for analysis. TA was converted to acceleration due to gravity (g), and GRF was normalised to bodyweight (BW). Foot-strike pattern was determined as the first part of the foot to contact the ground and assessed as either rearfoot or forefoot. Due to the small proportion of forefoot runners in this study, midfoot strikers were also classified as forefoot. Stride length was calculated using the set speed of the treadmill and the average cadence of the participant. PTA was calculated as the maximum vertical acceleration force for each stride. IP occurred identified as the maximum point of vGRF scaled by BW. Where IP was less obvious, it was identified at the minimum positive point of the loading rate curve at the first negative peak of PTA. Figure 1 outlines this method. VALR was calculated as the average slope of the curve between 20% and 80% of the time from initial contact to IP and scaled to BW. Vertical impulse was measured as an estimate of the area under the force–time curve as the sum of instantaneous axial GRF values for 100 time points. Time-series data from a representative subject that were used to calculate PTA, IP, VALR, VILR, and vertical impulse are shown in Figure 1.

Statistical analysis was conducted using Microsoft Excel (Microsoft Corporation, Redmond, WA, USA) and IBM SPSS Statistics (Statistical Package for the Social Sciences, Version 29.0.2.0, IBM Corp, Armonk, NY, USA). Mean values for each participant were compiled in a single spreadsheet, and group means were calculated using these values. Appropriate assumption testing was conducted accordingly prior to each stage of analysis. Repeated measures multivariate analyses of variance (MANOVA) and follow up repeated measures

analyses of variance (ANOVA) were conducted for speed and cadence to determine the significance of between-group mean differences. In the case of a significant effect, pairwise comparisons were interpreted, and partial eta-squared effect sizes were calculated to determine the weight of the findings. Strength of effect sizes were determined as weak ($\eta^2 = 0.01$), moderate ($\eta^2 = 0.06$), or strong ($\eta^2 = 0.14$). A series of mixed between-within subjects' ANOVAs were conducted to assess the impact of foot-strike pattern on vertical load. The between-subjects factor was habitual foot strike (habitual rearfoot vs. habitual forefoot), and the within-subjects factor was the foot-strike condition (preferred strike vs. forefoot strike vs. rearfoot strike). For the purpose of this study's scope, only main effects were interpreted. In the case of a significant effect, simple effects tests were conducted. Pearson product-moment correlation coefficients were conducted using the stride-by-stride data to examine the strength and direction of the relationships between running technique and vertical load. The strength of Pearson's correlations coefficients was determined as weak ($r < 0.3$), moderate ($r < 0.5$), or strong ($r > 0.5$).

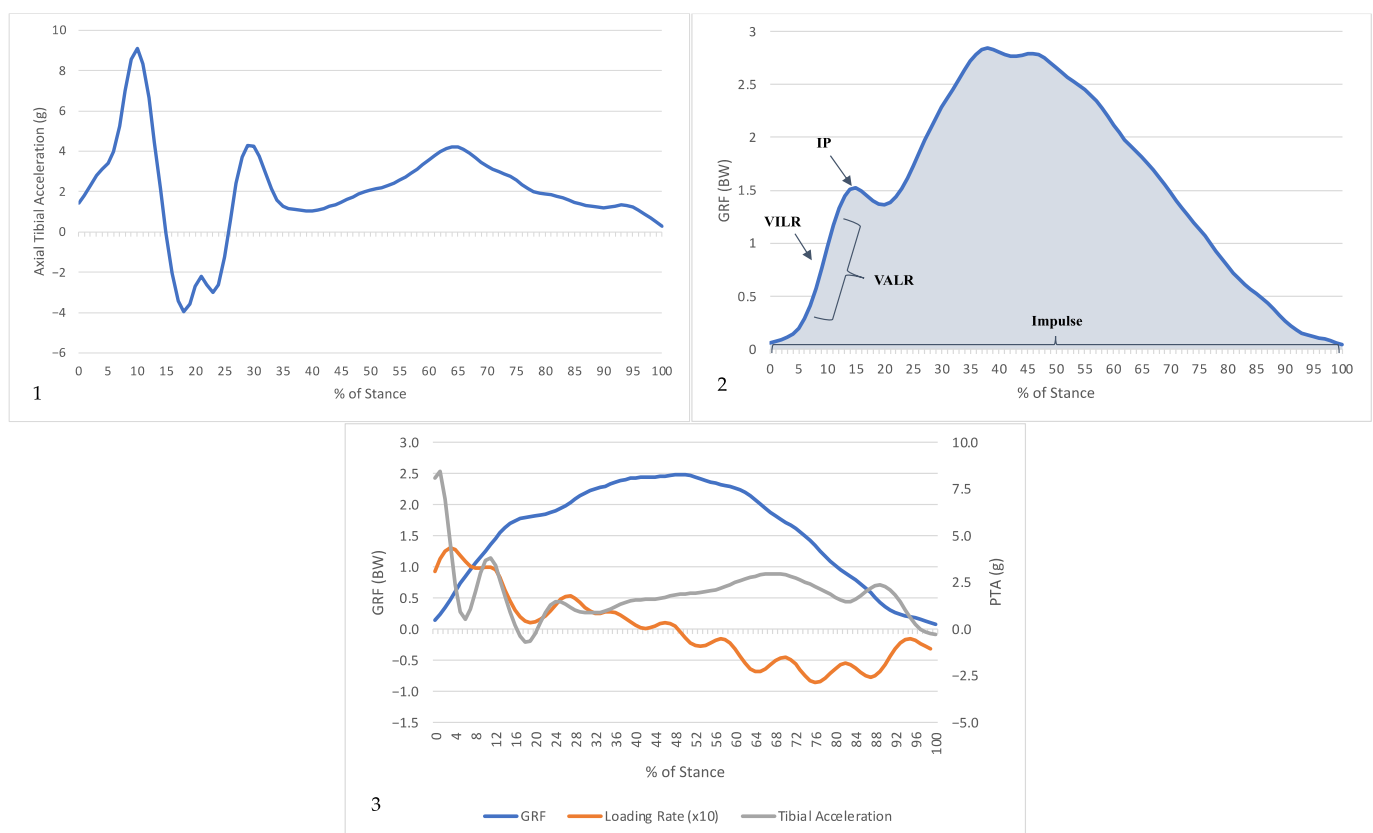


Figure 1. (1) Time-series data for a representative subject for peak tibial acceleration (PTA), (2) time-series data for a representative subject for impact peak (IP), vertical average loading rate (VALR), vertical instantaneous loading rate (VILR) and vertical impulse, (3) time-series data for a representative subject for impact peak with no obvious impact peak.

A machine-learning analysis was conducted using Orange Data Mining (University of Ljubljana, Slovenia) to evaluate the ability of machine-learning models to estimate vGRF metrics. Stride-by-stride data for BW, height, speed, cadence, stride length (normalised to height), and foot strike were input into the model. PTA data and participant number were included after the initial output to assess whether IMU data would be useful to improve the accuracy of the predictions, and to determine whether the models were simply learning the patterns for individual participants. Four machine-learning models were tested: gradient boosting; AdaBoost; random forest; and k-nearest neighbours (kNN). The models that

were selected are non-parametric, robust to outliers, and make no assumptions about the data distribution [45]. In line with previous methods, and to avoid overfitting, data were separated by stratified, replicable sampling into a 75% sample for model training, and a 25% sample for testing [32,46]. A 10-fold cross-validation method was applied to the training sample of the data to test the robustness of the models. Mean absolute percentage error (MAPE), and an r-squared (r^2) were used to quantify the accuracy and the proportion of variance explained by each model, and the most accurate model was selected for testing on the remaining 25% of the dataset. Shapley additive explanations (SHAP) was used to assess the importance of each aspect of running technique to the model's accuracy. Higher SHAP values represent a greater impact on the model, and positive/negative SHAP values represent the direction of influence on the model.

3. Results

Sixteen participants met the inclusion criteria and were included in the study (Table 1). A single participant's PTA values for the rearfoot condition were removed due to device malfunction; cases were excluded pairwise.

Table 1. Baseline participant descriptors.

	Mean	SD
Age (years)	21.69	1.62
Height (m)	1.74	0.08
Mass (kg)	70.75	10.32
Number of running activities > 15 min weekly	3.25	1.13
Months at current load	25.38	26.04
Average running distance per week (km)	16.25	8.19
Average running duration per week (min)	153.75	89.14

3.1. Primary Outcomes

3.1.1. Speed

The MANOVA showed statistically significant differences between preferred, fast, and slow speed conditions; Wilks' lambda = 0.057, $F(8, 8) = 16.64$, $p < 0.001$, $\eta^2 = 0.943$. Assumption testing revealed that VALR and VILR breached the assumption of multicollinearity, thus VALR was analysed using a separate one-way repeated measures ANOVA; Wilks' lambda = 0.440, $F(2, 14) = 8.909$, $p < 0.003$, multivariate $\eta^2 = 0.560$. PTA, VALR, VILR, and vertical impulse were significantly lower at 10% reduced speed compared to preferred speed (13%, 10.9%, 9.3%, and 3.2%, respectively). IP and vertical impulse were significantly higher at fast speed compared to preferred speed (5.8% and 2.6). All load metrics were significantly lower at slow speed compared to fast speed, with an 18.4% reduction in PTA, a 10.3% reduction in IP, a 12.7% reduction in VALR, an 11.6% reduction in VILR, and a 5.6% reduction in vertical impulse. Pairwise comparisons are shown in Table S1, and boxplots in Figure S1.

Pearson product-moment correlation coefficients revealed a weak, positive relationship between PTA and speed, $r = 0.215$, $n = 1110$, $p < 0.001$, a moderate positive correlation for IP, $r = 0.472$, $n = 1120$, $p < 0.001$, weak positive correlations for VALR and VILR, $r = 0.188$ and 0.224 , respectively, $n = 1120$, $p < 0.001$, and a moderate positive correlation for impulse, $r = 0.490$, $n = 1120$, $p < 0.001$.

3.1.2. Cadence

The MANOVA revealed a statistically significant difference between preferred, fast, and slow cadence conditions on the combined dependent variables; Wilks' lambda = 0.160,

$F(8, 8) = 5.234$, $p = 0.015$, $\eta^2 = 0.840$. The one-way repeated measures ANOVA for VALR showed a significant effect for cadence; Wilks' lambda = 0.453, $F(2, 14) = 8.455$, $p < 0.004$, $\eta^2 = 0.547$. Pairwise comparisons confirmed by follow-up one-way repeated measures ANOVAs showed that a 10% increase in cadence significantly decreased PTA, VALR, VILR, and vertical impulse by 11.5%, 15.6%, 13.5% and 3.5%, respectively, and a 10% decrease in cadence from the preferred significantly increased VALR, VILR, and impulse by 12.2%, +10.4%, and +3.6%, respectively. PTA, VALR, VILR, and impulse were significantly lower at slow than fast cadence (18.9%, 24.9%, 21.6%, and 6.8%, respectively). Pairwise comparisons are shown in Table S2 and boxplots in Figure S2.

There was a moderate, negative correlation between PTA and cadence, $r = -0.329$, $n = 1110$, $p < 0.001$, with increased cadence associated with decreased PTA. For IP, there was no significant correlation $p = 0.051$. For VALR and VILR, there were similar moderate and weak negative correlations, $r = -0.313$ and -0.271 , respectively, $n = 1120$, $p < 0.001$. For impulse, there was a weak negative correlation, $r = -0.276$, $n = 1120$, $p < 0.001$.

3.1.3. Stride Length

There was a moderate, positive correlation between PTA and stride length normalised to height, $r = 0.360$, $n = 1110$, $p < 0.001$, with increased stride length associated with increased PTA. For IP, there was a moderate positive correlation, $r = 0.437$, $n = 1120$, $p < 0.001$ and for VALR and VILR, there were similar moderate positive correlations, $r = 0.336$ and 0.341 , respectively, $n = 1120$, $p < 0.001$. For impulse, there was a strong positive correlation, $r = 0.516$, $n = 1120$, $p < 0.001$. Scatter plots are shown in Figure S3.

3.1.4. Foot-Strike Pattern

There were significant main effects for foot-strike pattern for PTA; Wilks' lambda = 0.187 $F(2, 12) = 26.05$, $p < 0.001$, $\eta^2 = 0.813$, VALR; Wilks' lambda = 0.176, $F(2, 13) = 30.491$, $p < 0.001$, $\eta^2 = 0.820$, VILR; Wilks' lambda = 0.140, $F(2, 13) = 39.87$, $p < 0.001$, $\eta^2 = 0.860$, and impulse; Wilks' lambda = 0.457, $F(2, 13) = 7.71$, $p = 0.006$, $\eta^2 = 0.543$. Simple effects tests and pairwise comparisons highlighted that a forefoot-strike pattern produced significantly lower vertical load than a rearfoot-strike pattern for PTA, VALR, and VILR (26.6%, 68.3%, and 68.9%, respectively). Impulse was significantly lower by 4.7% for rearfoot strikers. Vertical load rates for habitual forefoot strikers were significantly lower than habitual rearfoot strikers (VALR: 58.1% and VILR: 47.6%). Pearson's correlation coefficients determined a strong relationship between VALR and foot strike ($r = 0.654$, $n = 1120$, $p < 0.001$), VILR and foot strike ($r = 0.660$, $n = 1120$, $p < 0.001$) and a weak correlation between PTA and foot strike, ($r = -0.259$, $n = 1110$, $p < 0.001$) outlining that a rearfoot strike is associated with higher vertical loads. There was a moderate correlation between impulse and foot strike ($r = -0.334$, $n = 1120$, $p < 0.001$) that highlighted the opposite relationship. Estimated marginal means are shown in Figure S4.

3.2. Secondary Outcomes—Machine Learning Analysis

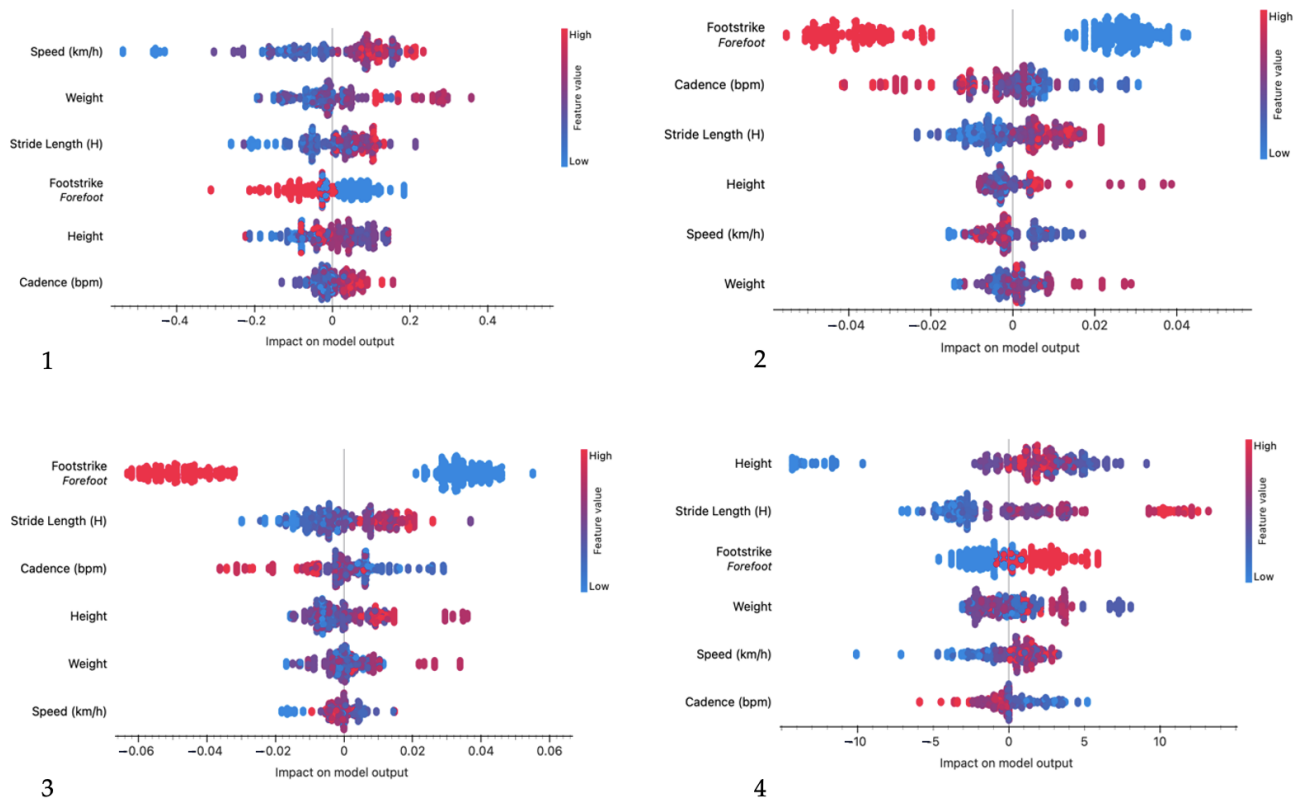
3.2.1. Impact Peak

For IP, cross-validation of the random forest model produced $r^2 = 0.608$, MAPE = 13% and testing on test data produced $r^2 = 0.701$, MAPE = 9.5%. The comparison between model outputs is displayed in Table 2. Speed and weight were key contributors to the model (Figure 2), adding participant number as a predictor made no change and including PTA values significantly reduced the accuracy of the model.

Table 2. Cross-validation output on 75% data sample for impact peak.

Model	MSE	RMSE	MAE	MAPE	R2
kNN	0.080	0.282	0.193	0.135	0.564
Gradient Boosting	0.072	0.268	0.181	0.130	0.607
Random Forest	0.072	0.268	0.181	0.130	0.608
AdaBoost	0.072	0.268	0.188	0.132	0.608

Key: MSE = mean square error, RMSE = root mean square error, MAE = mean average error, MAPE = mean average percentage error, R2 = r-squared.

**Figure 2.** Machine-learning model output—variable contributions for (1) impact peak, (2) vertical average loading rate, (3) vertical instantaneous loading rate and (4) vertical impulse.

3.2.2. Vertical Average Loading Rate

For VALR, cross-validation of the gradient boosting model produced $r^2 = 0.835$, MAPE = 10.5% and testing on test data produced $r^2 = 0.849$, MAPE = 10% (Table 3). Foot strike and cadence were key contributors (Figure 2), and the inclusion of participant or PTA made negligible change to the accuracy of the model.

Table 3. Cross-validation output on 75% data sample for vertical average loading rate.

Model	MSE	RMSE	MAE	MAPE	R2
kNN	0.000	0.021	0.015	0.112	0.816
Gradient Boosting	0.000	0.019	0.015	0.105	0.835
Random Forest	0.000	0.020	0.015	0.108	0.828
AdaBoost	0.000	0.020	0.015	0.109	0.824

Key: MSE = mean square error, RMSE = root mean square error, MAE = mean average error, MAPE = mean average percentage error, R2 = r-squared.

3.2.3. Vertical Instantaneous Loading Rate

For VILR, cross-validation for the gradient boosting model produced $r^2 = 0.794$, MAPE = 11.8% and testing on test data produced $r^2 = 0.798$, MAPE = 10.9% (Table 4).

Foot strike and cadence were key contributors (Figure 2); adding a participant made no change, but adding PTA made a very minor improvement to the accuracy of the model.

Table 4. Cross-validation output on 75% data sample for vertical instantaneous loading rate.

Model	MSE	RMSE	MAE	MAPE	R2
kNN	0.001	0.028	0.021	0.124	0.769
Gradient Boosting	0.001	0.026	0.020	0.118	0.794
Random Forest	0.001	0.027	0.021	0.119	0.790
AdaBoost	0.001	0.027	0.021	0.121	0.784

Key: MSE = mean square error, RMSE = root mean square error, MAE = mean average error, MAPE = mean average percentage error, R2 = r-squared.

3.2.4. Vertical Impulse

For vertical impulse, cross-validation for the gradient boosting model produced $r^2 = 0.737$, MAPE = 3.3% and testing on test data produced $r^2 = 0.720$, MAPE = 3.4% (Table 5). Height and stride length were key contributors to the model (Figure 2), and adding participant and PTA made negligible improvement to the accuracy when testing on test data.

Table 5. Cross-validation output on 75% data sample for vertical impulse.

Model	MSE	RMSE	MAE	MAPE	R2
kNN	51.273	7.161	5.004	0.033	0.722
Gradient Boosting	48.477	6.963	4.910	0.033	0.737
Random Forest	49.045	7.003	4.926	0.033	0.734
AdaBoost	53.427	7.309	5.181	0.034	0.711

Key: MSE = mean square error, RMSE = root mean square error, MAE = mean average error, MAPE = mean average percentage error, R2 = r-squared.

4. Discussion

The results of this trial demonstrate that significant increases in vertical load are associated with a 10% increase in speed, an increase in stride length, a reduction in cadence of 10%, and a rearfoot strike. In addition, they highlighted that a decrease in vertical load is associated with a reduction in speed of 10%, a reduction in stride length, a 10% increase in cadence, and a forefoot strike. The findings support the primary hypothesis. The results also highlight a strong relationship between speed, cadence, stride length, foot strike, height, and bodyweight with all four vGRF variables. Incorporating these into a gradient boosting model yielded an accurate method for estimating key vGRF metrics. This study provides a framework for gait-change intervention, and a method for estimating vertical load metrics to inform retraining methods.

A statistically significant difference between preferred, slow, and fast speeds was noted for estimates of tibial load, with a very large multivariate effect size. These findings build on those of Sheerin and colleagues [47] and Hunter et al. [41], who reported statistically significant differences in PTA and VALR across multiple speed conditions. The comparable weak linear correlation reported by Sheerin et al. highlights the need to account for individual variability for clinical application. The findings suggest that speed is a major determinant of vertical loading across different metrics, and they reinforce its probable role in influencing running mechanics and bone-stress-related injury risk. For cadence, statistically significant differences between preferred, slow, and fast cadence were noted for vertical load, with a very large multivariate effect size. Unlike previous studies from Keast et al. [48] and Yong et al. [49] who determined negligible changes, the present findings align with Willy et al. [50], and demonstrate that an increase in cadence of 10% can

significantly reduce vertical load rates. This study used a more diverse participant sample and incorporated IP as part of the loading rate analysis, offering a more comprehensive evaluation. Clinically, these results support cadence modification as a viable intervention to reduce vertical load rates and that it may be an effective method of managing MTSS. The findings for stride length were similar to cadence due to their well-documented inverse linear relationship, reported as Pearson's $r = -0.78$ [51]. Significant positive correlations reinforce the role of stride length as a determinant of tibial load. While prior studies from Derrick et al. [52] and Wang et al. [42], have reported similar trends, the present study demonstrates that a reduction in stride length through the manipulation of cadence and speed can effectively reduce vertical loading across multiple metrics. It suggests that clinically, these targeted strategies may be useful for the management of MTSS. The results for PTA and foot-strike pattern align with previous findings by Gruber et al. [53] and Ruder et al. [54], which demonstrated significant increases in PTA with rearfoot striking. However, the present study found no significant differences in IP between foot-strike patterns. This contrasts with prior studies, such as Boyer and Derrick [55] and Nordin et al. [56], likely due to the methodological differences in identifying the absence of a clear impact peak for forefoot strikers. The contrast between the findings for impulse and peak loads in the present study are likely explained by the earlier IP in forefoot strikers [56]. Research suggests that forefoot strikers activate plantar-flexor muscles 11% earlier and they remain activated 10% later than rearfoot strikers [57]. As vertical impulse includes the area under the active peak, the associated increase is likely due to increased muscle attenuation. Clinically, the findings suggest that while forefoot striking may reduce peak loads, it may prolong muscle activation, which could influence rehabilitation strategies for runners transitioning between foot-strike patterns.

The results from the machine learning analysis revealed that height, bodyweight, speed, cadence, stride length (normalised to height), and foot-strike pattern can be used to accurately estimate IP, VALR, VILR, and vertical impulse without the inclusion of PTA. Overall, the biggest contributors to the gradient boosting model were foot strike and stride length, which align with the earlier findings. The present study demonstrates that these variables provide similar MAPE values to accelerometer-driven machine-learning models [30–32] without requiring access to PTA measurements. The results build on the previous findings of Newman and coworkers [15] and Shaw and colleagues [16], who established the key risk factors for the development of MTSS and developed a predictive model using these factors to estimate military recruits' risk of developing the condition. The present study has now established a field-based method of estimating an individual's GRF metrics for prevention and provides a framework for intervention informed by vertical loads.

There are some limitations to this study. Firstly, there was no control group in this study and there is no consensus on clinically meaningful differences in vertical load metrics for MTSS. Gait retraining should, therefore, be implemented on an individual basis. This trial did not use follow-up to observe the long-term effects of gait changes. While previous research has linked a forefoot strike to increased rates of calf injuries and Achilles tendinopathy [58], others show conflicting results [59]. Further large-sample investigation is warranted. Secondly, the timeframes of an honours project did not allow for further data collection and may have reduced the strength of correlations. However, repeated measures were used for correlations and the machine-learning analysis (10 strides per condition per participant), which is shown to increase statistical power [60]. Additionally, the inclusion of only five forefoot strikers is representative of the general population (~6%) [61]. Including midfoot strikers in the forefoot group may have reduced the disparity in impulse and peak loads between rearfoot and forefoot. However, both forefoot and midfoot runners typically

have a significantly larger contact area than rearfoot runners [62] and it is common for studies to combine these groups to improve statistical power, due to these similarities in running styles [53,54]. It should also be noted that the vertical load metrics used in this study are not true measures of bone load. While strain gauges or musculoskeletal modelling could improve accuracy [18,41,63,64], these methods were not feasible within the scope of this study. Thirdly, normalising data to 101 data points per stride may have produced minor variations in loading rates and makes direct comparison with literature reporting in BW/s difficult. Stride length was calculated using the treadmill belt speed and average cadence, which does not account for small AP movements on foot contact and individual stride variation. Lastly, the study took place in a controlled laboratory. Tibial load metrics are subject to change in outdoor conditions with incline and surface [65,66], and newly learned gait patterns have also been demonstrated not to fully translate to running in a field environment [67]. Due to the popularity of overground and trail running, investigation of gait retraining with variations in surface and incline would be beneficial for real-world application.

The findings of this study suggest that runners can significantly reduce their vertical load by making 10% changes to speed and cadence, reducing the length of their stride, and transitioning to a forefoot strike. The machine-learning analysis provides a field-based algorithm for clinicians to implement these running technique changes with accurate estimates of how they can influence vGRF metrics. This study presents a cost-effective method of making informed load decisions by using easily accessible and measurable aspects of running technique, without requiring access to expensive treadmills. The results also highlight that IMU sensors are not required to increase the accuracy of these predictions. As the cohort of the study comprised primarily recreational runners, the findings suggest that gait retraining may be applicable to this population in addition to athletes and military personnel. Figure 3 highlights the relationship between speed, cadence, stride length, foot strike, and VALR (predicted by the random forest model) for a synthetic participant. The participant is 188 cm tall, weighs 76 kg, preferred speed 12 km/h, preferred cadence 160 spm, and a habitual rearfoot striker. The graph demonstrates that, by decreasing their preferred speed by 10%, they could reduce their VALR by ~7.5%. By increasing their cadence by 10%, they could reduce their VALR by ~9%. And, by switching to a forefoot strike, they could reduce their VALR by 49%.

Future research should investigate the relative importance of peak loads, loading rates, impulse, and their accumulation in the context of MTSS. Evidence from animal studies suggests that tibial fatigue is better explained by volume under strain rather than the magnitude of peak strain [22]. Exploration of these vGRF metrics in MTSS populations would be useful for the clinical application of gait retraining. Additionally, as most prospective research focuses on stress fracture, it would be valuable to establish clinically meaningful values and critical levels in MTSS populations. Due to the acknowledged limitations of bone-load estimates, a similar investigation of the present study using finite element analysis (FEA) would also be valuable. FEA has been used to investigate the mechanisms and probability of tibial stress fracture [39,63,64] by modelling areas of greatest stress. As MTSS is suggested to exist on a continuum with stress fracture [10] and is associated with cortical oedema and microtrauma [11], an investigation of tibial load using FEA is warranted. Finally, long-term studies are required to assess the retention of gait-retraining in outdoor environments and sloped conditions, and to better understand the potential adverse effects of technique change.

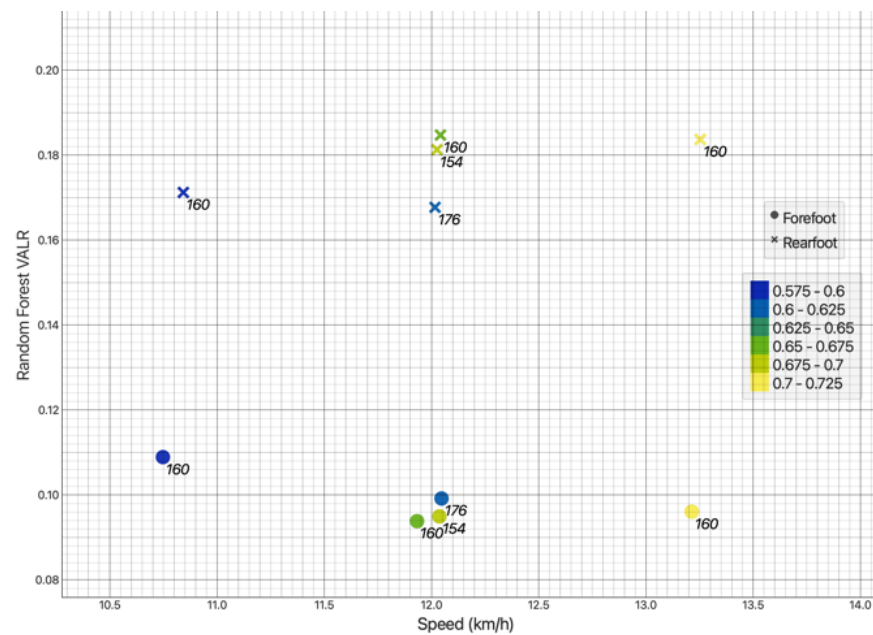


Figure 3. Synthetic participant speed, cadence, stride length, foot strike, and estimated vertical average loading rate—random forest model Key: italics = cadence (steps per minute), colour = stride length (normalised to height), symbol = foot strike.

5. Conclusions

This study suggests that clinicians can significantly reduce vertical load using small-scale changes to running technique, specifically, a 10% speed reduction (PTA, VALR, VILR, and vertical impulse), a 10% cadence increase (PTA, VALR, VILR, and impulse) and forefoot striking (PTA, VALR, and VILR). The results establish a practical, accessible, and affordable method of informing these load-based decisions by allowing clinicians to estimate changes to key vertical load metrics that can be achieved via gait retraining with 3.4% to 10.9% mean average error. Further research is required to assess the relative importance of peak loads, loading rates, and impulse for MTSS, and to determine clinically meaningful targets for a reduction in these metrics.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/biomechanics5020022/s1>, Table S1. Pairwise comparisons for peak tibial acceleration (PTA), impact peak (IP), vertical average loading rate (VALR), vertical instantaneous loading rate (VILR), and speed; Figure S1. Boxplots of speed and peak tibial acceleration (PTA), impact peak (IP), vertical average loading rate (VALR), vertical instantaneous loading rate (VILR), and vertical impulse. Key: *a* = sig. different to preferred, *b* = sig. different to slow, *c* = sig. different to fast, *X* = mean, ____ = median, *box* = quartiles, *whiskers* = range, *BW* = bodyweight; Table S2. Pairwise comparisons for peak tibial acceleration (PTA), impact peak (IP), vertical average loading rate (VALR), vertical instantaneous loading rate (VILR), and cadence; Figure S2. Boxplots of cadence and peak tibial acceleration (PTA), impact peak (IP), vertical average loading rate (VALR), vertical instantaneous loading rate (VILR), and vertical impulse. Key: *a* = sig. different to preferred, *b* = sig. different to slow, *c* = sig. different to fast, *X* = mean, ____ = median, *box* = quartiles, *whiskers* = range, *BW* = bodyweight; Figure S3. Scatter plots with regression lines for stride length (normalised to height) and peak axial tibial acceleration (PTA), vertical average loading rate (VALR), vertical instantaneous loading rate (VILR), and vertical impulse. Key: *g* = acceleration due to gravity, *BW* = bodyweight, *spm* = steps per minute; Figure S4. Estimated marginal means for foot strike and peak tibial acceleration (PTA), vertical average loading rate (VALR), vertical instantaneous loading rate (VILR), and vertical impulse.

Author Contributions: Conceptualisation, T.M. and P.N.; methodology, T.M., P.N. and C.R.R.; software, C.R.R.; validation, T.M., P.N. and C.R.R.; formal analysis, T.M., P.N. and C.R.R.; investigation, T.M., P.N., C.R.R., J.A.B. and J.W.; resources, P.N. and C.R.R.; data curation, T.M. and P.N.; writing—original draft preparation, T.M.; writing—review and editing, T.M., P.N., J.A.B., J.W. and C.R.R.; visualisation, T.M.; supervision, P.N., J.A.B., J.W. and C.R.R.; project administration, P.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Ethics approval was obtained from the University of Canberra, Human Research Ethics Committee, for a low-risk project involving humans, on 6 March 2024, Project Number 13393.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to ethical considerations.

Acknowledgments: Thank you to the University of Canberra Research Institute for Sport and Exercise for allowing use of the SportsTek lab, including the instrumented force-plate treadmill, inertial measurement units, and cameras.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Dai, S.; Carroll, D.D.; Watson, K.B.; Paul, P.; Carlson, S.A.; Fulton, J.E. Participation in Types of Physical Activities Among US Adults—National Health and Nutrition Examination Survey 1999–2006. *J. Phys. Act. Health* **2015**, *12* (Suppl. S1), S128–S140. [[CrossRef](#)] [[PubMed](#)]
2. Scheerder, J.; Breedveld, K.; Borgers, J. *Running Across Europe: The Rise and Size of One of the Largest Sport Markets*; Palgrave Macmillan: London, UK, 2015; pp. 1–268.
3. Lee, D.C.; Brellenthin, A.G.; Thompson, P.D.; Sui, X.; Lee, I.M.; Lavie, C.J. Running as a Key Lifestyle Medicine for Longevity. *Prog. Cardiovasc. Dis.* **2017**, *60*, 45–55. [[CrossRef](#)] [[PubMed](#)]
4. Hespanhol Junior, L.C.; Pillay, J.D.; van Mechelen, W.; Verhagen, E. Meta-Analyses of the Effects of Habitual Running on Indices of Health in Physically Inactive Adults. *Sports Med.* **2015**, *45*, 1455–1468. [[CrossRef](#)]
5. Fields, K.B.; Sykes, J.C.; Walker, K.M.; Jackson, J.C. Prevention of Running Injuries. *Curr. Sports Med. Rep.* **2010**, *9*, 176–182. [[CrossRef](#)]
6. Hreljac, A. Impact and overuse injuries in runners. *Med. Sci. Sports Exerc.* **2004**, *36*, 845–849. [[CrossRef](#)]
7. Kakouris, N.; Yener, N.; Fong, D.T.P. A systematic review of running-related musculoskeletal injuries in runners. *J. Sport Health Sci.* **2021**, *10*, 513–522. [[CrossRef](#)]
8. Deshmukh, N.S.; Phansopkar, P. Medial Tibial Stress Syndrome: A Review Article. *Cureus* **2022**, *14*, e26641. [[CrossRef](#)]
9. Moen, M.H.; Tol, J.L.; Weir, A.; Steunebrink, M.; De Winter, T.C. Medial tibial stress syndrome: A critical review. *Sports Med.* **2009**, *39*, 523–546. [[CrossRef](#)]
10. Galbraith, R.M.; Lavallee, M.E. Medial tibial stress syndrome: Conservative treatment options. *Curr. Rev. Musculoskelet. Med.* **2009**, *2*, 127–133. [[CrossRef](#)]
11. Franklyn, M.; Oakes, B. Aetiology and mechanisms of injury in medial tibial stress syndrome: Current and future developments. *World J. Orthop.* **2015**, *6*, 577–589. [[CrossRef](#)]
12. Menéndez, C.; Batalla, L.; Prieto, A.; Rodríguez, M.; Crespo, I.; Olmedillas, H. Medial Tibial Stress Syndrome in Novice and Recreational Runners: A Systematic Review. *Int. J. Environ. Res. Public Health* **2020**, *17*, 7457. [[CrossRef](#)] [[PubMed](#)]
13. Winters, M.; Eskes, M.; Weir, A.; Moen, M.H.; Backx, F.J.; Bakker, E.W. Treatment of Medial Tibial Stress Syndrome: A Systematic Review. *Sports Med.* **2013**, *43*, 1315–1333. [[CrossRef](#)] [[PubMed](#)]
14. Moen, M.H.; Holtslag, L.; Bakker, E.; Barten, C.; Weir, A.; Tol, J.L.; Backx, F. The treatment of medial tibial stress syndrome in athletes; a randomized clinical trial. *Sports Med. Arthrosc. Rehabil. Ther. Technol.* **2012**, *4*, 12. [[CrossRef](#)] [[PubMed](#)]
15. Newman, P.; Witchalls, J.; Waddington, G.; Adams, R. Risk factors associated with medial tibial stress syndrome in runners: A systematic review and meta-analysis. *Open Access J. Sports Med.* **2013**, *4*, 229–241. [[CrossRef](#)]
16. Shaw, A.; Newman, P.; Witchalls, J.; Hedger, T. Externally validated machine learning algorithm accurately predicts medial tibial stress syndrome in military trainees: A multicohort study. *BMJ Open Sport Exerc. Med.* **2023**, *9*, e001566. [[CrossRef](#)]

17. Sheerin, K.R.; Reid, D.; Besier, T.F. The measurement of tibial acceleration in runners—A review of the factors that can affect tibial acceleration during running and evidence-based guidelines for its use. *Gait Posture* **2019**, *67*, 12–24. [\[CrossRef\]](#)
18. Burr, D.B.; Milgrom, C.; Fyhrie, D.; Forwood, M.; Nyska, M.; Finestone, A.; Hoshaw, S.; Saia, E.; Simkin, A. In vivo measurement of human tibial strains during vigorous activity. *Bone* **1996**, *18*, 405–410. [\[CrossRef\]](#)
19. Zandbergen, M.A.; Ter Wengel, X.J.; van Middelaar, R.P.; Buurke, J.H.; Veltink, P.H.; Reenalda, J. Peak tibial acceleration should not be used as indicator of tibial bone loading during running. *Sports Biomech.* **2023**, *16*, 1–18. [\[CrossRef\]](#)
20. Scott, R.; James, R.; Barnett, C.T.; Sale, C.; Varley, I. Perspectives from research and practice: A survey on external load monitoring and bone in sport. *Front. Sports Act. Living* **2023**, *5*, 1150052. [\[CrossRef\]](#)
21. Milner, C.E.; Ferber, R.; Pollard, C.D.; Hamill, J.; Davis, I.S. Biomechanical factors associated with tibial stress fracture in female runners. *Med. Sci. Sports Exerc.* **2006**, *38*, 323–328.
22. Haider, I.T.; Lee, M.; Page, R.; Smith, D.; Edwards, W.B. Mechanical fatigue of whole rabbit-tibiae under combined compression-torsional loading is better explained by strained volume than peak strain magnitude. *J. Biomech.* **2021**, *122*, 110434. [\[CrossRef\]](#)
23. Napier, C.; Maclean, C.L.; Maurer, J.; Taunton, J.E.; Hunt, M.A. Kinetic risk factors of running-related injuries in female recreational runners. *Scand. J. Med. Sci. Sports* **2018**, *28*, 2164–2172. [\[CrossRef\]](#) [\[PubMed\]](#)
24. Meardon, S.A.; Derrick, T.R.; Willson, J.D.; Baggaley, M.; Steinbaker, C.R.; Marshall, M.; Willy, R.W. Peak and Per-Step Tibial Bone Stress During Walking and Running in Female and Male Recreational Runners. *Am. J. Sports Med.* **2021**, *49*, 2227–2237. [\[CrossRef\]](#) [\[PubMed\]](#)
25. Van Hooren, B.; van Rengs, L.; Meijer, K. Per-step and cumulative load at three common running injury locations: The effect of speed, surface gradient, and cadence. *Scand. J. Med. Sci. Sports* **2024**, *34*, e14570. [\[CrossRef\]](#)
26. Greenhalgh, A.; Sinclair, J.; Protheroe, L.; Chockalingam, N. Predicting impact shock magnitude: Which ground reaction force variable should we use. *Int. J. Sports Sci. Eng.* **2012**, *6*, 225–231.
27. Hennig, E.M.; LaFortune, M.A. Relationships between ground reaction force and tibial bone acceleration parameters. *J. Appl. Biomech.* **1991**, *7*, 303–309.
28. Tenforde, A.S.; Hayano, T.; Jamison, S.T.; Outerleys, J.; Davis, I.S. Tibial Acceleration Measured from Wearable Sensors Is Associated with Loading Rates in Injured Runners. *PM&R* **2020**, *12*, 679–684. [\[CrossRef\]](#)
29. Pohl, M.B.; Mullineaux, D.R.; Milner, C.E.; Hamill, J.; Davis, I.S. Biomechanical predictors of retrospective tibial stress fractures in runners. *J. Biomech.* **2008**, *41*, 1160–1165.
30. Bach, M.M.; Dominici, N.; Daffertshofer, A. Predicting vertical ground reaction forces from 3D accelerometry using reservoir computers leads to accurate gait event detection. *Front. Sports Act. Living* **2022**, *4*, 1037438. [\[CrossRef\]](#)
31. Kiernan, D.; Ng, B.; Hawkins, D.A. Acceleration-Based Estimation of Vertical Ground Reaction Forces during Running: A Comparison of Methods across Running Speeds, Surfaces, and Foot Strike Patterns. *Sensors* **2023**, *23*, 8719. [\[CrossRef\]](#)
32. Scheltinga, B.L.; Kok, J.N.; Buurke, J.H.; Reenalda, J. Estimating 3D ground reaction forces in running using three inertial measurement units. *Front. Sports Act. Living* **2023**, *5*, 1176466. [\[CrossRef\]](#) [\[PubMed\]](#)
33. Ohmi, T.; Aizawa, J.; Hirohata, K.; Ohji, S.; Mitomo, S.; Ohara, T.; Yagishita, K. Biomechanical characteristics of the lower extremities during running in male long-distance runners with a history of medial tibial stress syndrome: A case control study. *BMC Musculoskelet. Disord.* **2023**, *24*, 103. [\[CrossRef\]](#) [\[PubMed\]](#)
34. Zimmermann, W.; Linschoten, C.; Beutler, A. Gait retraining as part of the treatment programme for soldiers with exercise-related leg pain: Preliminary clinical experiences and retention. *S. Afr. J. Sports Med.* **2017**, *29*, 1–6. [\[CrossRef\]](#)
35. Diebal, A.R.; Gregory, R.; Alitz, C.; Gerber, J.P. Forefoot running improves pain and disability associated with chronic exertional compartment syndrome. *Am. J. Sports Med.* **2012**, *40*, 1060–1067. [\[CrossRef\]](#)
36. Yates, B.; White, S. The incidence and risk factors in the development of medial tibial stress syndrome among naval recruits. *Am. J. Sports Med.* **2004**, *32*, 772–780. [\[CrossRef\]](#)
37. Giandolini, M.; Horvais, N.; Rossi, J.; Millet, G.Y.; Samozino, P.; Morin, J.-B. Foot strike pattern differently affects the axial and transverse components of shock acceleration and attenuation in downhill trail running. *J. Biomech.* **2016**, *49*, 1765–1771. [\[CrossRef\]](#)
38. Chan, Z.Y.S.; Zhang, J.H.; Ferber, R.; Shum, G.; Cheung, R.T.H. The effects of midfoot strike gait retraining on impact loading and joint stiffness. *Phys. Ther. Sport* **2020**, *42*, 139–145. [\[CrossRef\]](#)
39. Gaudette, L.W.; Bradach, M.M.; de Souza Junior, J.R.; Heiderscheit, B.; Johnson, C.D.; Posilkin, J.; Rauh, M.J.; Sara, L.K.; Wasserman, L.; Hollander, K.; et al. Clinical Application of Gait Retraining in the Injured Runner. *J. Clin. Med.* **2022**, *11*, 6497. [\[CrossRef\]](#)
40. Faul, F.; Erdfelder, E.; Lang, A.-G.; Buchner, A. G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav. Res. Methods* **2007**, *39*, 175–191. [\[CrossRef\]](#)
41. Hunter, J.G.; Garcia, G.L.; Shim, J.K.; Miller, R.H. Fast Running Does Not Contribute More to Cumulative Load than Slow Running. *Med. Sci. Sports Exerc.* **2019**, *51*, 1178–1185. [\[CrossRef\]](#)
42. Wang, J.; Luo, Z.; Dai, B.; Fu, W. Effects of 12-week cadence retraining on impact peak, load rates and lower extremity biomechanics in running. *PeerJ* **2020**, *8*, e9813. [\[CrossRef\]](#) [\[PubMed\]](#)

43. Winter, D.A. *Biomechanics and Motor Control of Human Movement*; John Wiley & Sons: Hoboken, NJ, USA, 2009.
44. Bates, B.; Osternig, L.; Sawhill, J.; James, S. An assessment of subject variability, subject-shoe interaction, and the evaluation of running shoes using ground reaction force data. *J. Biomech.* **1983**, *16*, 181–191. [[PubMed](#)]
45. Hastie, T.; Tibshirani, R.; Friedman, J.H. *The Elements of Statistical Learning Data Mining, Inference, and Prediction*, 2nd ed.; Springer: New York, NY, USA, 2009.
46. Derie, R.; Robberechts, P.; Van den Berghe, P.; Gerlo, J.; De Clercq, D.; Segers, V.; Davis, J. Tibial Acceleration-Based Prediction of Maximal Vertical Loading Rate During Overground Running: A Machine Learning Approach. *Front. Bioeng. Biotechnol.* **2020**, *8*, 33. [[CrossRef](#)]
47. Sheerin, K.R.; Besier, T.F.; Reid, D. The influence of running velocity on resultant tibial acceleration in runners. *Sports Biomech.* **2020**, *19*, 750–760. [[CrossRef](#)]
48. Keast, A.; Bonacci, J.; Fox, A. Acute effects of gait interventions on tibial accelerations during treadmill running. *J. Sci. Med. Sport* **2022**, *25*, S63–S64. [[CrossRef](#)]
49. Yong, J.R.; Silder, A.; Montgomery, K.L.; Fredericson, M.; Delp, S.L. Acute changes in foot strike pattern and cadence affect running parameters associated with tibial stress fractures. *J. Biomech.* **2018**, *76*, 1–7. [[CrossRef](#)]
50. Willy, R.W.; Buchenic, L.; Rogacki, K.; Ackerman, J.; Schmidt, A.; Willson, J.D. In-field gait retraining and mobile monitoring to address running biomechanics associated with tibial stress fracture. *Scand. J. Med. Sci. Sports* **2016**, *26*, 197–205. [[CrossRef](#)]
51. Hunter, J.P.; Marshall, R.N.; McNair, P.J. Interaction of step length and step rate during sprint running. *Med. Sci. Sports Exerc.* **2004**, *36*, 261–271.
52. Derrick, T.R.; Hamill, J.; Caldwell, G.E. Energy absorption of impacts during running at various stride lengths. *Med. Sci. Sports Exerc.* **1998**, *30*, 128–135.
53. Gruber, A.H.; Boyer, K.A.; Derrick, T.R.; Hamill, J. Impact shock frequency components and attenuation in rearfoot and forefoot running. *J. Sport Health Sci.* **2014**, *3*, 113–121. [[CrossRef](#)]
54. Ruder, M.; Jamison, S.T.; Tenforde, A.; Mulloy, F.; Davis, I.S. Relationship of Foot Strike Pattern and Landing Impacts during a Marathon. *Med. Sci. Sports Exerc.* **2019**, *51*, 2073–2079. [[CrossRef](#)] [[PubMed](#)]
55. Boyer, E.R.; Derrick, T.R. Lower extremity joint loads in habitual rearfoot and mid/forefoot strike runners with normal and shortened stride lengths. *J. Sports Sci.* **2018**, *36*, 499–505. [[CrossRef](#)] [[PubMed](#)]
56. Nordin, A.D.; Dufek, J.S.; Mercer, J.A. Three-dimensional impact kinetics with foot-strike manipulations during running. *J. Sport Health Sci.* **2017**, *6*, 489–497. [[CrossRef](#)]
57. Ahn, A.N.; Brayton, C.; Bhatia, T.; Martin, P. Muscle activity and kinematics of forefoot and rearfoot strike runners. *J. Sport Health Sci.* **2014**, *3*, 102–112. [[CrossRef](#)]
58. Molloy, J.M. Factors Influencing Running-Related Musculoskeletal Injury Risk Among U.S. Military Recruits. *Mil. Med.* **2016**, *181*, 512–523. [[CrossRef](#)]
59. Daoud, A.I.; Geissler, G.J.; Wang, F.; Saretsky, J.; Daoud, Y.A.; Lieberman, D.E. Foot strike and injury rates in endurance runners: A retrospective study. *Med. Sci. Sports Exerc.* **2012**, *44*, 1325–1334. [[CrossRef](#)]
60. Goulet, M.-A.; Cousineau, D. The Power of Replicated Measures to Increase Statistical Power. *Adv. Meth. Pract. Psychol. Sci.* **2019**, *2*, 199–213. [[CrossRef](#)]
61. Kasmer, M.E.; Liu, X.-C.; Roberts, K.G.; Valadao, J.M. Foot-Strike Pattern and Performance in a Marathon. *Int. J. Sports Physiol. Perform.* **2013**, *8*, 286–292. [[CrossRef](#)]
62. Hayes, P.; Caplan, N. Foot strike patterns and ground contact times during high-calibre middle-distance races. *J. Sports Sci.* **2012**, *30*, 1275–1283. [[CrossRef](#)]
63. Edwards, B.; Taylor, D.; Rudolphi, T.J.; Gillette, J.C.; Derrick, T.R. Effects of running speed on a probabilistic stress fracture model. *Clin. Biomech.* **2010**, *25*, 372–377. [[CrossRef](#)]
64. Edwards, W.B.; Taylor, D.; Rudolphi, T.J.; Gillette, J.C.; Derrick, T.R. Effects of stride length and running mileage on a probabilistic stress fracture model. *Med. Sci. Sports Exerc.* **2009**, *41*, 2177–2184. [[CrossRef](#)] [[PubMed](#)]
65. Firminger, C.R.; Vernillo, G.; Savoldelli, A.; Stefanyshyn, D.J.; Millet, G.Y.; Edwards, W.B. Joint kinematics and ground reaction forces in overground versus treadmill graded running. *Gait Posture* **2018**, *63*, 109–113. [[CrossRef](#)] [[PubMed](#)]
66. Gottschall, J.S.; Kram, R. Ground reaction forces during downhill and uphill running. *J. Biomech.* **2005**, *38*, 445–452. [[CrossRef](#)] [[PubMed](#)]
67. Zhang, J.H.; Chan, Z.Y.S.; Au, I.P.H.; An, W.W.; Cheung, R.T.H. Can runners maintain a newly learned gait pattern outside a laboratory environment following gait retraining? *Gait Posture* **2019**, *69*, 8–12. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.