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Foot Angle and Loading Rate during Running Demonstrate a Nonlinear Relationship

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Foot Angle and Loading Rate during Running Demonstrate a Nonlinear Relationship

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ABSTRACT

Vertical loading rates are typically found to be lower in forefoot compared to rearfoot strikers, promoting the idea that forefoot striking is desirable and may reduce running injury risk. However, prior work using linear models has shown that foot inclination angle at initial contact (FIA) is a poor predictor of vertical loading rate, suggesting a more complex association exists.

PURPOSE: To determine if a non-linear model superiorly describes the relationship between FIA and average vertical loading rate (AVLR). Secondary analyses assessed the influence of sex and sport on the association between FIA and AVLR.

METHODS: Whole body kinematics and vertical ground reaction forces were collected for 170 healthy NCAA Division I athletes (97 males; 81 cross country runners) during treadmill running at 2.68, 3.35, and 4.47 m/s. FIA and AVLR were calculated for 15 strides and averaged across strides for each limb. Polynomial mixed effects models assessed linear and non-linear trends in the relationship between FIA and AVLR across the entire sample and accounting for sex and sport participation.

RESULTS: AVLR was lowest at the extremes of FIA (i.e., -15°, 20°), while greater AVLRs were observed between 5-10°. The cubic model resulted in a significantly better fit than the linear model ($p < 0.001$). AVLR was also more variable among FIA associated with rear- and midfoot strike than forefoot strike. Adding sex to the model did not influence model fit; though, controlling for sport minimally improved model fit.

CONCLUSIONS: The relationship between FIA and AVLR is best represented by a cubic model. Consequently, FIA should be treated as a continuous variable. Reducing FIA into categories may misrepresent the relationship between FIA and other gait variables.

KEY WORDS: Gait, Biomechanics, Foot Inclination Angle, Foot Strike

Introduction

Assessments of running mechanics are often performed to estimate the loads a runner may be experiencing and, ultimately, determine the potential for injury. In particular, foot strike is often evaluated as it is considered by many to be a primary determinant of lower limb mechanics during running.(1, 2) Foot inclination angle (FIA), a quantitative measure of foot strike, is defined by the angle between the foot and ground at initial contact, with rearfoot strike patterns having greater (more positive) angles.(3) Foot inclination angle is so strongly believed to influence running mechanics that previous investigations have excluded individuals with certain FIA patterns (e.g. rearfoot, forefoot) from study enrollment entirely in an attempt to ensure outcomes were not influenced by FIA.(4-7)

Vertical loading rate (VLR), a frequent focus of studies assessing risk factors for running-related injuries, has been found to be lower in forefoot compared to rearfoot strikers,(6-11) fostering the belief that forefoot strike is preferred. However, a similar number of studies have shown no significant relationship with foot strike pattern and VLR.(12-14) The inconsistencies in the predictive effect of dichotomous foot strike categorization (forefoot versus rearfoot) on loading rate indicate a linear model may not best describe the association between FIA and VLR. Indeed, previous work has shown that FIA is a very poor predictor of VLR when using a linear model (R^2 = 0.04),(15) suggesting a more complex relationship between FIA and VLR is present. Consequently, simplifying foot angle into discrete groups, such as rearfoot and forefoot, is likely to misrepresent the true relationship between FIA and VLR. Additionally, the assumption of a linear relationship between FIA and VLR has clinical implications, as transitioning a patient towards smaller FIA in an attempt to reduce VLR may not actually result in the desired change.

The primary aim of this investigation was to determine if a curvilinear model superiorly described the relationship between FIA and VLR compared to a linear model. Secondary aims were to assess the influence of sex and sport on the relationship between FIA and VLR. We hypothesized the relationship between FIA and VLR would be more accurately described using curvilinear methods and that sex and sport would not change the relationship between FIA and VLR.

Methods

This study reviewed running gait data from 2015-2018 in the Badger Athletic Performance database. The database contains results from a standardized battery of pre-season assessments, including gait analysis, athletes undergo each year while at the University of Wisconsin-Madison. The records review was approved by the University's Health Sciences Institutional Review Board. Data for a given athlete were extracted if the athlete: 1) was cleared for full participation at time of testing; 2) had running data available at 2.68, 3.35, and 4.47 m/s (10, 8, and 6 min/mile, respectively); 3) had no history of lower-extremity surgery; and 4) had no history of lower-extremity bone stress injuries within 3 months before or after the testing session. Surgical and bone stress injury history were obtained via self-report and confirmed via medical record review when possible. Surgical and bone stress injury history prior to testing were confirmed in the medical record for 57 athletes; bone stress injury history following testing was confirmed in the medical record for all athletes. If an athlete had multiple eligible data collection sessions from sequential years, a session was selected for inclusion at random to reduce any potential effects of maturation and training. This resulted in 170 athlete records being included in the final dataset (Figure 1).

Our sample was comprised of a diverse range of sports (cross country, football, soccer, and basketball). Given the notable difference in the directionality and time spent running between cross country and the other sports included in this study, our analyses categorized athletes as cross country (e.g. single-direction sport) or non-cross country (e.g. multi-direction sports) for the purposes of assessing the effect of sport.

Data Acquisition and Processing

Whole body kinematics were collected using 42 reflective markers placed on the body segments of each subject, 23 of which were located on anatomical landmarks. Markers were placed by the same researcher (MRSJ) for all data collections. The treadmill assessment was completed per a standardized testing protocol. Athletes first walked for a minimum of two minutes to acclimate to the treadmill and motion capture setup. The athletes then ran at 2.68, 3.35, and 4.47 m/s, in that order. Fifteen seconds of data for each speed was recorded after the athlete had acclimated to the speed for at least 30 seconds. A static standing position was also recorded to establish static posture for normalization of foot angle during running.(15)

Kinematic data from the running trials were recorded at 200 Hz using an 8-camera passive marker system (Motion Analysis Corporation, Santa Rosa, CA). Three-dimensional ground reaction forces and moments were synchronously recorded at 2000 Hz using an instrumented treadmill (Bertec Corporation, Columbus, OH). Kinematic data were low-pass filtered using a bi-directional, 4th order Butterworth filter with a cutoff frequency of 12 Hz. Ground reaction forces were low-pass filtered using a bi-directional, 3rd order Butterworth filter with a cutoff frequency of 50 Hz. Foot contact and toe-off times were identified as the frame when the vertical ground reaction force went above and fell below 50 N, respectively.(3)

The body was modeled as a 14-segment, 31 degrees-of-freedom (DOF) articulated linkage. Anthropometric properties of body segments were scaled to each individual using the subject's height, mass, and segment lengths.(16) The hip joint was modeled as a ball and socket with three DOF. The knee joint was represented as a one DOF joint, in which the tibiofemoral translations and non-sagittal rotations were constrained functions of the knee flexion-extension angle.(17) The ankle-subtalar complex was represented by two revolute joints aligned with the anatomical axes.(18) For each stride, the generalized coordinates of the model were calculated at each time step using a global optimization inverse kinematics routine to minimize the weighted sum of squared differences between the measured and the model marker positions.(19)

Foot inclination angle was calculated as the resultant angle formed by the modelled foot segment and the horizontal plane at the frame of initial contact.(15) Foot angle was normalized to the foot position recorded from a standing static trial for each subject.(15) Average VLR (AVLR) was calculated as the slope between 20-80% of the magnitude of the vertical ground reaction force between initial contact and the impact peak (Figure 2). The magnitude of the force at 30.79% of the time to active peak was used in instances where the impact peak was not present as recommended by previous research.(20) All signal processing and data analysis was conducted using custom script developed in MATLAB Release 2018a (The Mathworks, Inc., Natick, MA).

Statistical Analyses

Polynomial mixed effects models were used to assess the appropriateness of a curvilinear trend in the relationship between FIA and AVLR. Data from both limbs were included in the analyses at three differing speeds (2.68, 3.35, and 4.47m/s), resulting in six measurements per participant. The mixed effects models accounted for the within-subject limb and speed correlation induced by the repeated measures via an unstructured covariance matrix for the left and right limb and an exchangeable covariance structure for the varying speeds. Each athlete was additionally modeled with a random effect. Linear, quadratic, and cubic terms for FIA were modelled and model fit was assessed via Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and likelihood ratio tests (LRT). These three approaches measure model fit slightly differently, with differing penalization criteria; thus, consistency across all three measures helps to inform the best fitting model. The actual magnitude of the AIC and BIC values cannot be meaningfully interpreted without comparing the values to another model. Smaller values of AIC and BIC indicate better fitting models, with differences between models of 2-4 points being considering a notable change and differences greater than 10 points indicating strong evidence of a better fitting model.(21) The LRT compares the goodness of fit of two nested models by comparing the ratio of the models' likelihoods to a chi-square distribution. In this study, LRTs compared quadratic and cubic models to linear models, respectively. Due to differing mean models (e.g. models with different covariates and numbers of covariates), maximum likelihood estimation was used for parameter estimation and likelihood comparison. Fixed effects estimates, values that maximize the likelihood of a model, were used to construct the curves and identify potential non-linear associations between FIA and AVLR. The impact (e.g. interaction) of sex and sport (cross country versus non-cross country) on the association between FIA and AVLR was also assessed. All modelling was conducted using SAS v9.4 (SAS Institutes, Cary, NC) and figures were created using MATLAB Release 2018a (The Mathworks, Inc., Natick, MA).

Results

Demographic information for the 170 athletes (97 males; 81 cross country) included in the analyses is provided in Table 1. Model fit statistics for each model (linear, quadratic, cubic) estimating AVLR from FIA are provided in Table 2. The cubic model resulted in a significantly better fit than the linear model via the LRT ($\chi^2 = 43.8$, df = 1; $p < 0.001$, Figure 3). Moreover, the AIC and BIC values were lowest for the cubic model fit and were 141.9 and 135.7 points lower than the linear model, respectively, again indicating a substantially better fit. Fixed effects estimates for each term of the linear, quadratic, and cubic model are provided in Table 3. The significant quadratic and cubic terms further support that a non-linear model better represents the association between FIA and AVLR.

Adding sex to the model did not result in statistically significant changes in model fit; in fact, model fit criteria were less predictive with sex included in the model (See Table, Supplemental Digital Content 1, which shows model comparisons with sex included as a covariate, http://links.lww.com/MSS/B606). Moreover, all main effect terms for sex and the accompanying interaction were not significant (see Table, Supplemental Digital Content 2, which shows fixed effects for models with sex included as a covariate, http://links.lww.com/MSS/B607). Although sport (cross country versus non-cross country) did influence the fit of the quadratic and cubic models, as evidenced by statistically significant interactions between FIA and sport (see Table, Supplemental Digital Content 1, which shows fixed effects for models with sport included as a covariate, http://links.lww.com/MSS/B606), the shape of the curve did not change from the original model (without sport), as indicated by the consistent direction of the quadratic and cubic estimates (see Table, Supplemental Digital Content 2, which describes fixed effects estimates, http://links.lww.com/MSS/B607). Full results for models assessing sex and sport are presented in the Supplemental Digital Content (see Tables, Supplemental Digital Content 1 and 2, which describe model fit parameters and fixed effects estimates for models controlling for sex and sport, http://links.lww.com/MSS/B606 and http://links.lww.com/MSS/B607).

Discussion

The purpose of this study was to determine if non-linear modeling approaches were superior to linear approaches when describing the relationship between FIA and AVLR. Our results showed that AVLR was indeed low among FIA typically associated with forefoot striking (FIA < 0^{o}) as previously described.(7, 11, 22) However, AVLR varied considerably among FIA associated with mid- and rearfoot striking (FIA > 0^{o}), such that a linear model did not best describe the relationship between the two gait variables. When comparing linear and curvilinear models for the entire sample of data, the cubic model was superior to both the linear and quadratic model in estimating AVLR from FIA (Table 2). This is supported by lower AIC, BIC, and LRT values observed for the cubic model, indicating a better model fit.

The relationship between FIA and AVLR was similar across speeds (Table, Supplemental Digital Content 3 and 4, which describe model fit parameters and fixed effects estimates, respectively, for each speed, http://links.lww.com/MSS/B608 and http://links.lww.com/MSS/B609); however, AVLR was observed to increase considerably with speed across the entire range of observed FIA values, with the greatest AVLR values occurring among FIA between -5^{o} and +10^{o} at all speeds (Figure 3).

Previous research suggests sport-specific participation influences a variety of performance measures,(23, 24) thus we performed a secondary analysis controlling for the effect of sport (cross-country versus non-cross country) as a covariate in the models estimating AVLR from FIA. The sport model comparisons followed the results observed for the entire sample, with the cubic model demonstrating a superior fit to both the linear and quadratic models after accounting for sport participation (see Table, Supplemental Digital Content 1, which describes model fit parameters, http://links.lww.com/MSS/B606 and Figure, Supplemental Digital Content 5, which shows the predicted AVLR by sport, http://links.lww.com/MSS/B610). Among athletes who demonstrated an FIA associated with more extreme forefoot striking (< -10^{o}), predicted AVLR for cross-country athletes was greater than non-cross country athletes. This result is likely due to 14-18% of cross country athletes in this sample exhibiting FIA less than -10^{o} at a given speed, while only 6-8% of non-cross country athletes exhibited FIA less than -10^{o}. Among FIA from -10^{o} to +25^{o}, there was no appreciable difference in predicted AVLR between athletes with similar FIA but different sport status.

Secondary analyses were also performed to assess the influence of sex on the relationship between FIA and AVLR, as a multitude of running mechanics have been shown to differ between sexes.(25, 26) When including sex as a covariate in the models, the cubic model was still identified as a more appropriate model compared to the linear and quadratic models, with no obvious difference in predicted AVLR between male and female athletes demonstrating similar

FIA (see Table, Supplemental Digital Content 1, which describes model fit parameters and Figure, Supplemental Digital Content 6, which shows the predicted AVLR by sex, http://links.lww.com/MSS/B611).

Previous research has demonstrated varying ability to predict AVLR from FIA when utilizing a linear model, with FIA alone explaining 4% of the variance in AVLR at a runner's preferred speed(15) and still only 26% of the variance when controlling for running speed.(27) As our data suggests a linear model does not appropriately describe the relationship between FIA and AVLR, it is likely that previous research utilizing linear models has underestimated the relationship between FIA and AVLR.(15, 27) Transforming FIA into discrete categories may similarly misrepresent the relationship between FIA and AVLR, which may explain the inconsistent findings of previous research relating FIA and AVLR to injury incidence. Based on the data presented in the current study, it is recommended that FIA be treated as a continuous variable.

Foot inclination angle is often utilized as a screening tool to estimate AVLR; however, the relationships found in the present study show AVLR varies considerably within a given FIA, particularly among FIA associated with midfoot and rearfoot striking. Application of this relationship suggests that modification of FIA through clinical gait retraining strategies cannot predictably attenuate forces sustained during the loading response. For example, transitioning individuals from an extreme rearfoot strike to a slight rearfoot or midfoot strike is often advocated as a method to reduce AVLR.(1, 28) Based on the findings of this study, in instances where the primary goal of gait retraining is to reduce loading rates, encouraging rearfoot strikers to transition to a midfoot strike is very likely to result in an increase, not a reduction, in loading rate, which is consistent with previous findings.(29) It is important to note, however, that there are a variety of gait retraining targets other than AVLR for which modification of extreme FIA towards more neutral values may be warranted, such as reduced knee flexion at initial contact or excessive hip adduction.(3) As modification of these gait retraining targets has implications for treatment of clinical pathologies, such as iliotibial band syndrome(30) and patellofemoral pain,(31) gait retraining strategies should be implemented on a patient-specific basis.

The generalizability of this study is limited to the characteristics of the athletes analyzed, including sport participation and preferred FIA pattern. We assessed the relationship between FIA and AVLR among collegiate football, soccer, basketball, and cross country athletes. While it is reasonable to expect that a similar non-linear relationship between FIA and AVLR would exist among recreational athletes, as well as athletes participating in other sports, this relationship should be investigated among a wider variety of athletic populations. Our sample was also comprised of approximately 30% FIA associated with forefoot striking (< 0^{o}) and 70% FIA associated with rearfoot striking. While this was not unexpected based on previous research reporting generally low rates (2-30%) of forefoot striking among a variety of running populations,(29, 32, 33) further refinement of the models presented in this study among a sample including more individuals demonstrating FIA less than 0^{o} (forefoot strike) would be beneficial. Several methods exist for calculating AVLR in the absence of an impact peak, with no one widely-accepted, gold-standard approach. Our approach has been shown to result in AVLR values that are highly comparable to those defined using 13% of stance phase or peak braking force.(20) Lastly, although AVLR is commonly assessed and related to FIA, there are other GRF characteristics which have demonstrated relationships with FIA, such as instantaneous loading rate, peak vertical GRF, vertical impact peak, and braking impulse, which were not assessed in this study. The linearity of the relationships between FIA and these variables should be evaluated by future investigations.

Conclusions

The relationship between FIA and AVLR is clearly non-linear, with the lowest AVLR values observed among FIA associated with extreme forefoot striking and AVLR being highly variable among FIA associated with mid- and rearfoot striking. Future investigations involving FIA and AVLR should utilize non-linear methods. Additionally, FIA should be treated as a continuous variable whenever possible, as reducing FIA into categories may misrepresent the relationship between FIA and other gait variables.

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Conflict of Interest

All authors declare no conflicts of interest.

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Figure Captions

Figure 1. Flowchart demonstrating processes used for the final selection of 170 athletes included in this study.

*The lower extremity was defined as the pelvis and all areas distal from the pelvis.

†Bone stress injury (BSI) history was considered within 3 months before or after the testing session.

^Speeds required for inclusion were 2.68, 3.35, and 4.47 m/s (10, 8, and 6 min/mile, respectively).

Figure 2a-b. Representative vertical ground reaction force tracings for A) individuals presenting with an impact peak and B) individuals presenting without an impact peak. The diamond represents the impact peak location (Figure 2A) or the derived impact peak location (Figure 2B) based on 30.79% of the time to peak vertical ground reaction force (square). The horizontal lines represent the area corresponding to 20-80% of the magnitude of the force between initial contact and impact peak, over which average vertical loading rate was calculated.

Figure 3. Scatterplot showing foot inclination angle and average vertical loading rate (AVLR) for all athletes during treadmill running at 2.68, 3.35, and 4.47m/s. The predicted AVLR across all speeds using a linear model is represented by the red line, while the predicted AVLR across all speeds utilizing a cubic model is represented by the blue line. The cubic model (Akaike Information Criterion (AIC): 13471.2; Bayesian Information Criterion (BIC): 13496.3; Negative Log Likelihood (NLL): 13455.2) provided a superior fit to the data compared to the linear model (AIC: 13613.1; BIC: 13632.0; NLL: 13601.1).

Figure 1

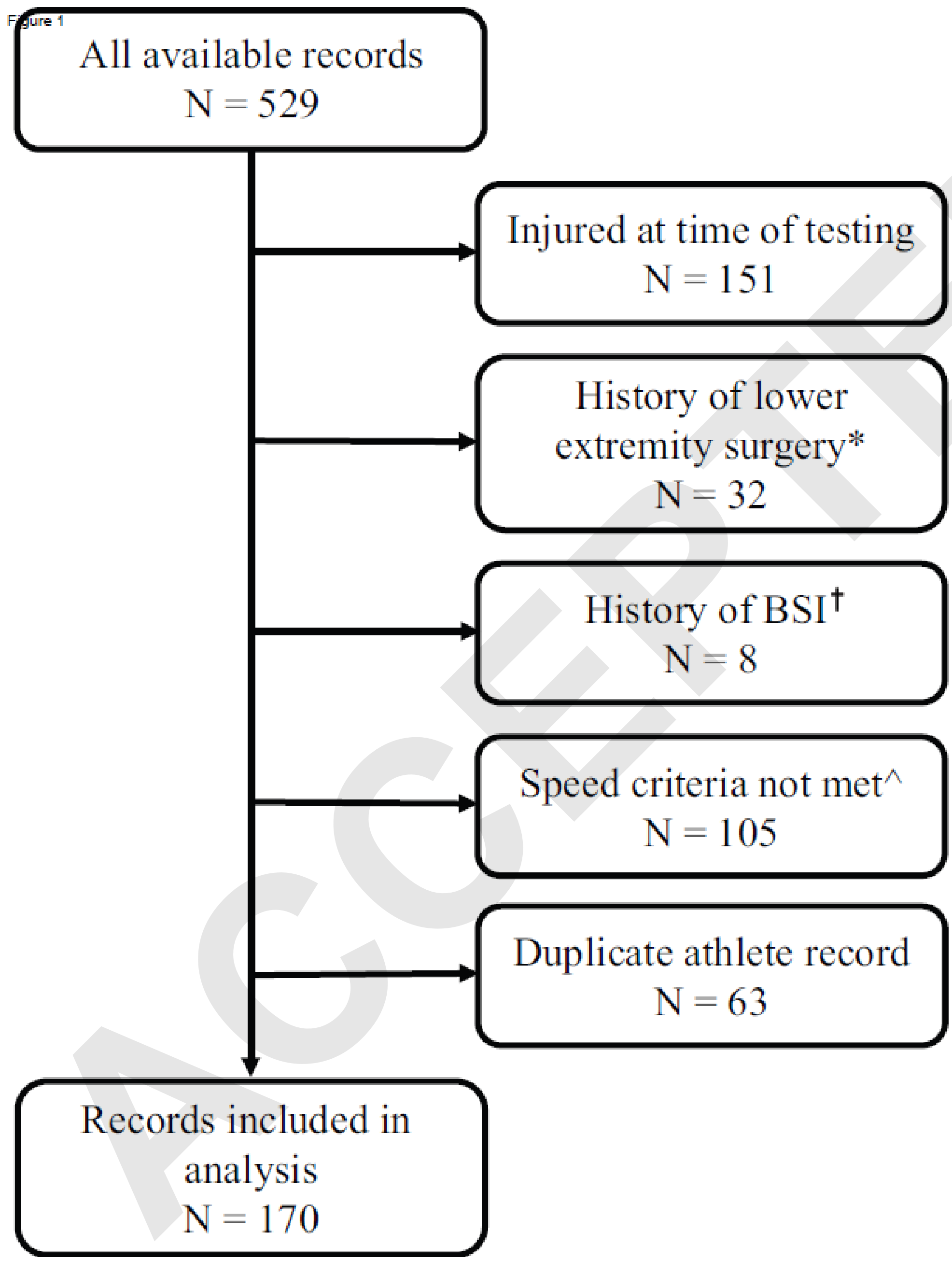


Figure 1
All available records
N = 529
Injured at time of testing
N = 151
History of lower extremity surgery*
N = 32
History of BSI†
N = 8
Speed criteria not met^
N = 105
Duplicate athlete record
N = 63
Records included in analysis
N = 170

Figure 2

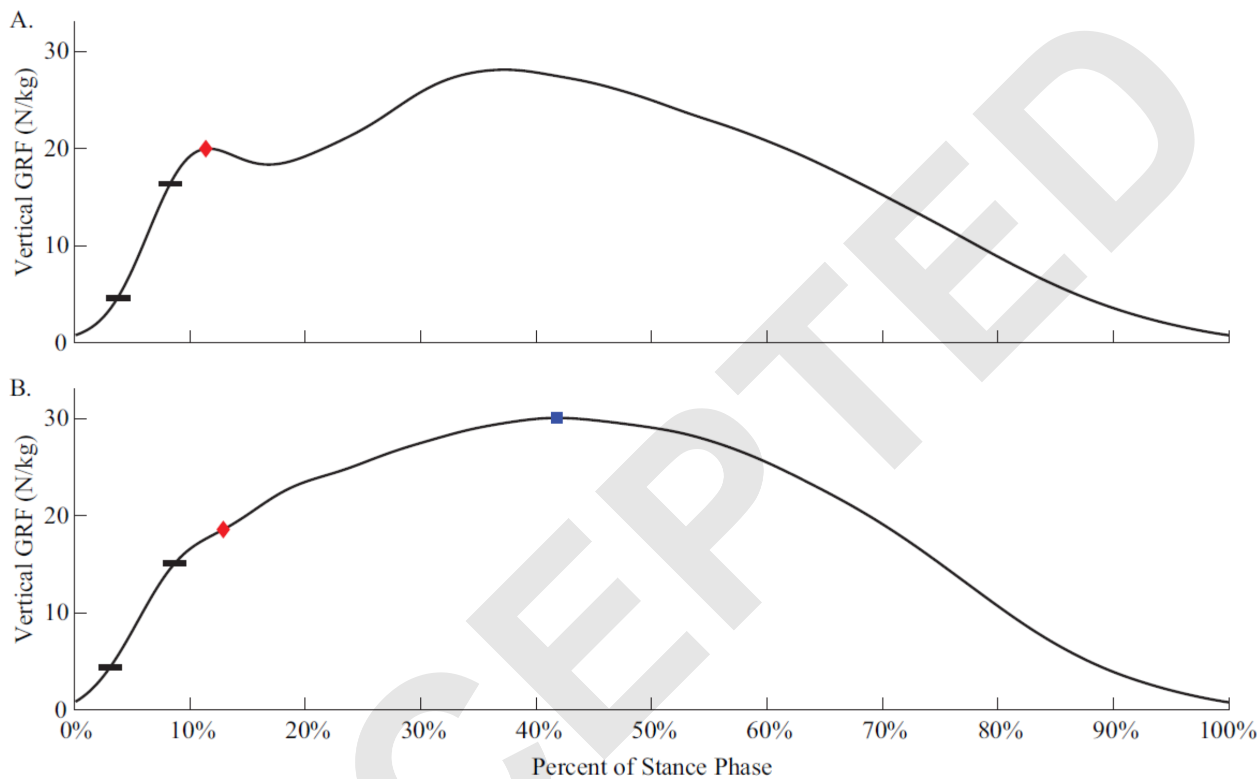
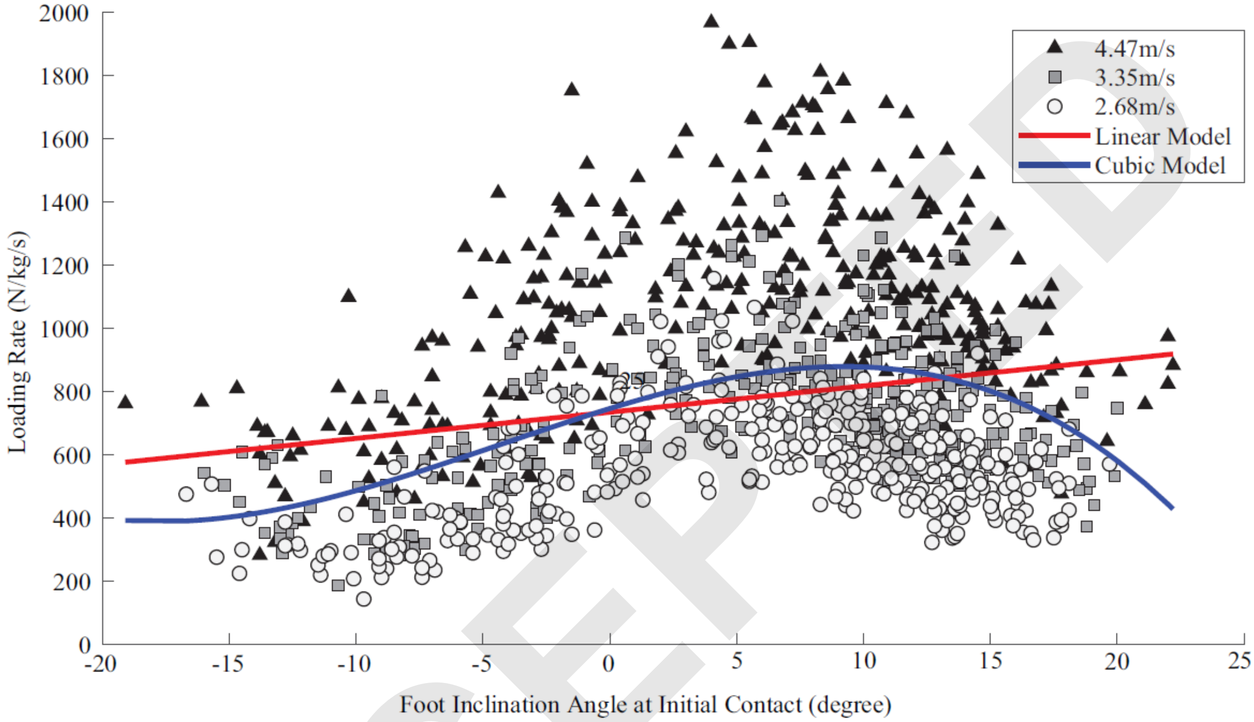

A.
30
20
10
0
Vertical GRF (N/kg)
B.
30
20
10
0
Vertical GRF (N/kg)
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Percent of Stance Phase

Figure 3



2000
1800
1600
1400
1200
1000
800
600
400
200
0
Loading Rate (N/kg/s)
-20
-15
-10
-5
0
5
10
15
20
25
Foot Inclination Angle at Initial Contact (degree)
4.47m/s
3.35m/s
2.68m/s
Linear Model
Cubic Model

Table 1. Descriptive demographics for 170 athletes included in this study. Non-cross country data was comprised of women's soccer, women's basketball, and football athletes.

	N	Age (years)	Height (m)	Weight (kg)
Women	73	19.4 ± 1.4	1.67 ± 0.06	60.7 ± 7.6
Cross Country	44	19.8 ± 1.4	1.66 ± 0.05	56.8 ± 5.4
Non-Cross Country	29	18.7 ± 0.9	1.70 ± 0.08	66.6 ± 6.7
Men	97	19.1 ± 1.2	1.83 ± 0.06	83.6 ± 14.7
Cross Country	37	20.0 ± 1.2	1.80 ± 0.06	68.5 ± 5.2
Non-Cross Country	60	18.6 ± 0.7	1.85 ± 0.06	92.7 ± 10.4

Table 2. Model comparison of a linear, quadratic, and cubic model fit of the relationship between foot inclination angle at initial contact (FIA) and average vertical loading rate (AVLR) The model included FIA as a continuous, independent predictor of AVLR.

Model	Mean Parameters (N)*	AIC	BIC	Negative Log Likelihood	χ^2/df**
Linear	3	13613.1	13632.0	13601.1	Ref
Quadratic	4	13513.1	13535.0	13499.0	102.1/1
Cubic	5	13471.2	13496.3	13455.2	43.8/1

AIC - Akaike Information Criterion, smaller value indicates better fit

BIC - Bayesian Information Criterion, smaller value indicates better fit

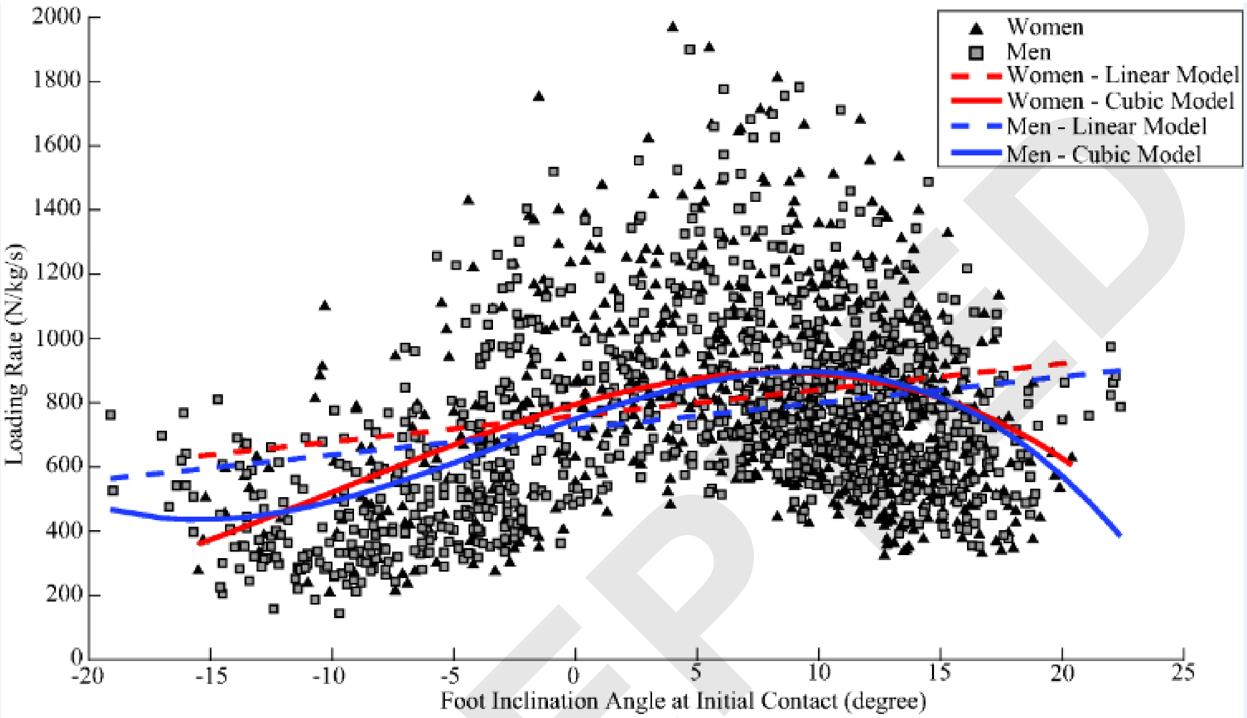
*Covariance parameters stayed constant in all models

**All likelihood ratio tests were significant at $p < 0.05$, with both the quadratic and cubic models statistically favored over the linear (null) model, respectively.

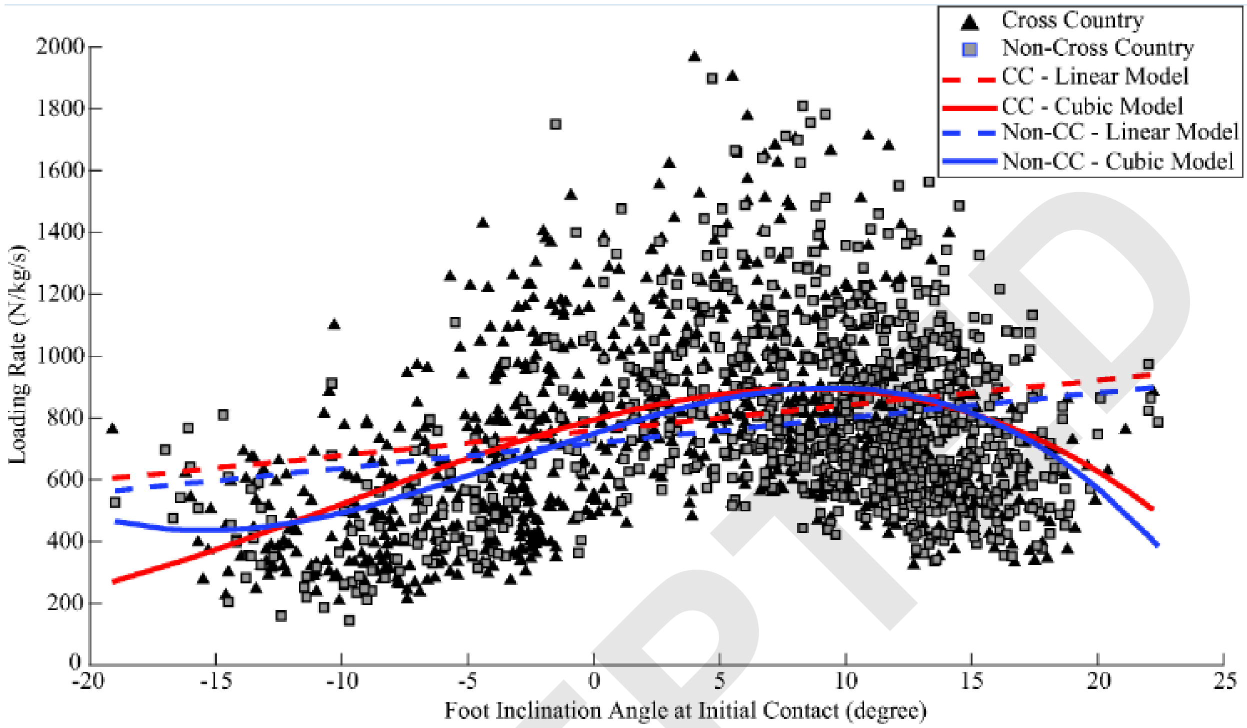
Table 3. Fixed effects for a linear, quadratic, and cubic model fit of the relationship between foot inclination angle at initial contact (FIA) and average vertical loading rate (AVLR) The model included FIA as a continuous, independent predictor of AVLR. Fixed effects are the parameter estimate values that maximize the model likelihood and thus result in the best fitting curve for this data.

Model Terms	**Linear**	**Quadratic**	**Cubic**
Intercept	734.98 (20.67)	799.74 (20.27)	764.45 (20.66)
FIA	8.28 (1.42)*	16.73 (1.56)*	24.54 (1.91)*
FIA^2	--	-1.05 (0.10)*	-0.64 (0.11)*
FIA^3	--	--	-0.05 (0.01)*

*Significant model term, $p < 0.001$.



Supplemental Digital Content 6. Figure
Scatterplot showing foot inclination angle and average vertical loading rate (AVLR) for men and women, collapsed across running speed. The predicted AVLR for each sex using a linear model are represented by the dashed lines, while the predicted AVLR utilizing a cubic model are represented by the solid lines. The cubic model provided a superior fit to the data (Akaike Information (AIC):



Supplemental Digital Content 5. Figure
Scatterplot showing foot inclination angle and average vertical loading rate (AVLR) for sport (cross-country (CC) versus non-cross country(Non-CC)), collapsed across running speed. The predicted AVLR for each sport using a linear model are represented by the dashed lines, while the predicted AVLR utilizing a cubic model are represented by the solid lines. The cubic model provided a superior fit to the

Supplemental Digital Content 1. Table

Model comparison of a linear, quadratic, and cubic model fit of the relationship between foot inclination angle at initial contact (FIA) and average vertical loading rate. Model 1 includes FIA as a continuous, independent predictor variable. Model 2 includes FIA as a predictor variable and sex as a covariate. Model 3 includes FIA as a predictor variable and sport (cross country, non-cross country) as a covariate.

	Linear	Quadratic	Cubic
Model 1 - FIA			
Number of Mean Parameters*	3	4	5
AIC	13613.1	13513.1	13471.2
BIC	13632.0	13535.0	13496.3
Negative Log Likelihood	13601.1	13499.0	13455.2
χ^2/df	Ref	102.1/1**	43.8/1**
Model 2 – FIA + Sex			
Number of Mean Parameters	4	7	9
AIC	13614.0	13517.8	13475.1
BIC	13636.0	13549.2	13512.7
Negative Log Likelihood	13600.0	13497.8	13451.1
χ^2/df	Ref	102.2/3**	46.7/2**
Model 3 – FIA + Sport			
Number of Mean Parameters	4	7	9
AIC	13615.0	13497.5	13468.3
BIC	13636.9	13528.9	13505.9
Negative Log Likelihood	13601.0	13477.5	13444.3
χ^2/df	Ref	123.5/3**	33.2/2**

AIC - Akaike Information Criterion

BIC - Bayesian Information Criterion

*Covariance parameters stayed constant in all models.

**Model comparisons were significantly different from linear reference model at $p < 0.001$.

Supplemental Digital Content 2. Table

Fixed effects estimates (SD) of a linear, quadratic, and cubic model fit of the relationship between foot inclination angle at initial contact (FIA) and average vertical loading rate. Model 1 includes FIA as a continuous, independent predictor variable. Model 2 includes FIA and sex as independent predictor variables. Model 3 includes FIA and sport (cross country, non-cross country) as independent predictor variables.

	Linear	**Quadratic**	**Cubic**
Model 1 - FIA			
Intercept	734.98 (20.67)	799.74 (20.27)	764.45 (20.66)
FIA	8.28 (1.42)**	16.73 (1.56)**	24.54 (1.91)**
FIA^2	--	-1.05 (0.10)**	-0.64 (0.11)**
FIA^3	--	--	-0.05 (0.01)**
Model 2 – FIA + Sex			
Intercept	718.36 (25.98)	784.87 (26.31)	749.30 (26.73)
FIA	8.11 (1.43)**	16.26 (1.92)**	26.13 (2.39)**
Sex (Female)	40.76 (38.83)	33.97 (41.49)	44.89 (42.95)
FIA^2	--	-0.98 (0.13)**	-0.55 (0.14)**
FIA*Sex	--	1.27 (3.35)	-4.70 (4.02)
FIA^2*Sex	--	-0.19 (0.21)	-0.34 (0.25)
FIA^3	--	--	-0.06 (0.01)**
FIA^3*Sex	--	--	0.03 (0.02)
Model 3 – FIA + Sport			
Intercept	727.15 (29.01)	798.49 (30.34)	770.66 (32.14)
FIA	8.39 (1.46)**	23.94 (2.59)**	26.05 (2.75)**
Sport	15.02 (39.22)	-23.81 (42.20)	2.12 (42.91)
FIA^2	--	-1.56 (0.15)**	-1.22 (0.22)**
FIA*Sport	--	-9.83 (3.32)*	-0.70 (3.97)
FIA^2*Sport	--	0.98 (0.21)**	0.74 (0.26)*
FIA^3	--	--	-0.02 (0.01)**
FIA^3*Sport	--	--	-0.04 (0.02)*

*Significant term in the model at $p < 0.01$; **Significant term in the model at $p < 0.001$

Supplementary Digital Content 3. Table

Model comparison of a linear, quadratic, and cubic model fit of the relationship between foot inclination angle at initial contact (FIA) and average vertical loading rate for each speed included in the analysis. Model 1 includes FIA as a continuous, independent predictor variable. Model 2 includes FIA as a predictor variable and sex as a covariate.

		2.68 m/s			**3.35 m/s**			**4.47 m/s**		
		Linear	**Quadratic**	**Cubic**	**Linear**	**Quadratic**	**Cubic**	**Linear**	**Quadratic**	**Cubic**
Model 1 FIA	**# Mean Parameters**	3	4	5	3	4	5	3	4	5
	AIC	4258.2	4192.9	4169.9	4402.0	4339.1	4317.9	4635.7	4562.1	4542.1
	BIC	4280.1	4193.3	4198.1	4423.9	4364.2	4346.1	4657.7	4587.1	4570.3
	Negative Log Likelihood	4244.2	4176.9	4151.9	4388.0	4323.1	4299.9	4621.7	4546.1	4524.1
	χ^2/df	Ref	67.3/1	25.0/1	Ref	64.9/1	23.2/1	Ref	75.6/1	22.0/1
Model 2 FIA + Sex	**# Mean Parameters**	4	7	9	4	7	9	4	7	9
	AIC	4260.1	4197.4	4170.6	4403.1	4339.2	4320.3	4634.3	4556.3	4539.9
	BIC	4285.2	4231.9	4211.1	4428.1	4373.7	4361.1	4659.4	4590.8	4580.7
	Negative Log Likelihood	4244.1	4175.4	4144.6	4387.1	4317.2	4294.3	4618.3	4534.3	4513.9
	χ^2/df	Ref	68.7/3	30.8/2	Ref	69.9/3	22.9/2	Ref	84.0/3	20.4/2

AIC - Akaike Information Criterion

BIC - Bayesian Information Criterion

Supplementary Digital Content 4. Table

Fixed effects estimates (SD) of a linear, quadratic, and cubic model fit of the relationship between foot inclination angle at initial contact (FIA) and average vertical loading rate. Model 1 includes FIA as a continuous, independent predictor variable. Model 2 includes FIA and sex as independent predictor variables.

		2.68 m/s			**3.35 m/s**			**4.47 m/s**		
Model	**Model terms**	**Linear**	**Quadratic**	**Cubic**	**Linear**	**Quadratic**	**Cubic**	**Linear**	**Quadratic**	**Cubic**
Model 1 FIA	INTERCEPT	515.92 (13.89)	578.14 (13.72)	553.05 (13.84)	675.90 (17.52)	752.72 (17.51)	714.83 (18.56)	1002.84 (24.31)	1108.67 (23.42)	1071.13 (23.99)
	FIA	7.27 (1.23)**	12.91 (1.24)**	19.77 (1.76)**	7.62 (1.53)**	15.41 (1.61)**	22.92 (2.18)**	12.03 (2.16)**	22.64 (2.18)**	31.58 (2.82)**
	FIA^2	---	-0.90 (0.10)**	-0.61 (0.11)**	--	-1.12 (0.13)**	-0.63 (0.16)**	--	-1.58 (0.17)**	-1.08 (0.19)**
	FIA^3	---	---	-0.05** (0.01)	--	--	-0.05 (0.01)**	--	--	-0.06 (0.01)**
Model 2 FIA + Sex	INTERCEPT	513.88 (17.03)	574.75 (18.04)	45.46 (17.73)	664.62 (21.13)	727.29 (22.51)	693.86 (23.23)	970.95 (11.25)	1054.78 (28.81)	1021.05 (28.99)
	FIA	7.24 (1.23)**	13.46 (1.52)**	23.70 (2.33)**	7.41 (1.54)**	16.78 (1.94)**	24.81 (2.72)**	11.25 (2.18)**	21.28 (2.54)**	31.97 (3.43)**
	SEX (Female)	5.10 (24.63)	10.33 (27.70)	23.29 (27.76)	29.16 (30.71)	69.97 (35.47)	62.86 (38.15)	83.05 (44.33)	140.03 (47.03)*	148.61 (50.67)
	FIA^2	---	-0.85 (0.13)**	-0.48 (0.14)**	---	-1.00 (0.17)**	-0.53 (0.20)*	--	-1.25 (0.20)**	-0.79 (0.21)**
	FIA*SEX	---	1.35 (2.64)	-8.14 (3.58)*	---	-4.62 (3.45)	-6.15 (4.56)	--	5.55 (4.99)	-1.91 (6.09)
	FIA^2*SEX	---	-0.12 (0.21)	-0.34 (0.23)	---	-0.22 (0.26)	-0.20 (0.33)	--	-1.11 (0.37)*	-1.10 (0.54)
	FIA^3	---	---	-0.07 (0.01)**	---	---	-0.06 (0.01)**	--	--	-0.06 (0.01)**
	FIA^3*SEX	---	---	0.04 (0.02)*	---	---	0.01 (0.02)	--	--	0.02 (0.04)

*Significant term in the model at $p < 0.01$; **Significant term in the model at $p < 0.001$