Journal of Biomechanics 73 (2018) 201–209

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

Accelerometer-based prediction of running injury in National Collegiate Athletic Association track athletes

Dovin Kiernan [a], David A. Hawkins [a,b,*], Martin A.C. Manoukian [b], Madeline McKallip [b], Laura Oelsner [c], Charles F. Caskey [a], Crystal L. Coolbaugh [a]

[a] Biomedical Engineering Graduate Group, University of California Davis, United States
[b] Department of Neurobiology, Physiology, & Behavior, University of California Davis, United States
[c] Department of Biomedical Engineering, University of California Davis, United States

ARTICLE INFO

Article history:
Accepted 1 April 2018

Keywords:
Ground reaction forces
Cumulative loading
Wearable sensors
Activity monitors

ABSTRACT

Running-related injuries (RRI) may result from accumulated microtrauma caused by combinations of high load magnitudes (vertical ground reaction forces; vGRFs) and numbers (strides). Yet relationships between vGRF and RRI remain unclear – potentially because previous research has largely been constrained to collecting vGRFs in laboratory settings and ignoring relationships between RRI and stride number. In this preliminary proof-of-concept study, we addressed these constraints: Over a 60-day period, each time collegiate athletes ($n = 9$) ran they wore a hip-mounted activity monitor that collected accelerations throughout the entire run. Accelerations were used to estimate peak vGRF, number of strides, and weighted cumulative loading (sum of peak vGRFs weighted to the 9th power) across the entirety of each run. Runners also reported their post-training pain/fatigue and any RRI that prevented training. Across 419 runs and >2.1 million strides, injured ($n = 3$) and uninjured ($n = 6$) participants did not report significantly different pain/fatigue ($p = 0.56$) or mean number of strides per run ($p = 0.91$). Injured participants did, however, have significantly greater peak vGRFs ($p = 0.01$) and weighted cumulative loading per run ($p < 0.01$). Results from this small but extensively studied sample of elite runners demonstrate that loading profiles (load magnitude-number combinations) quantified with activity monitors can provide valuable information that may prove essential for: (1) testing hypotheses regarding overuse injury mechanisms, (2) developing injury-prediction models, and (3) designing and adjusting athlete- and loading-specific training programs and feedback.

1. Introduction

Long distance runners experience high rates of running-related injury (RRI), musculoskeletal overuse injuries causing a restriction of running speed, distance, duration, or frequency (Hreljac, 2004). Depending on the population studied and the methods used to diagnose injury, incidences range from 6.9 to 92.4% per 1000 h of running (van Gent et al., 2007; Lopes et al., 2012; Videbæk et al., 2015). In addition to negatively affecting performance, these RRIs lead to both direct (e.g., health care), and indirect (e.g., time lost) costs (Hespanhol Junior et al., 2016). With approximately 51.5 million Americans running (The Outdoor Foundation, 2016) these injuries constitute a large health and economic burden. Thus, developing means to predict and prevent RRI can have meaningful health and economic impacts.

Overuse injuries such as RRI result from bouts of cyclic loading that cause microtrauma accumulation over time. When microtrauma from a given bout of loading is limited and biological structures are allowed adequate time for repair, they can positively remodel, becoming stronger and less susceptible to injury (e.g., Burr et al., 2002; Shepherd and Screen, 2013). In contrast, when successive bouts of cyclic loading occur before microtrauma can be repaired, microtrauma accumulation overwhelms repair processes, elicits negative remodeling, and increases injury risk (Fig. 1) (Rolf, 1995; Frost, 1998; Edwards et al., 2009; 2010). In single bouts of continuous cyclic loading, the relationship between load magnitude and the number of loading cycles to structure failure can be described by an inverse exponential relationship for soft tissue (Weightman et al., 1978; Wren et al., 2003) and an inverse power relationship for bone (Carter & Caler, 1985). In running, vertical ground reaction forces (vGRFs) are often used as surrogate

* Corresponding author at: One Shields Avenue, University of California Davis, College of Biological Sciences, Department of Neurobiology, Physiology, & Behavior, Room 196 Briggs Hall, Davis, CA 95616, United States.

E-mail address: dahawkins@ucdavis.edu (D.A. Hawkins).

https://doi.org/10.1016/j.jbiomech.2018.04.001
0021-9290/

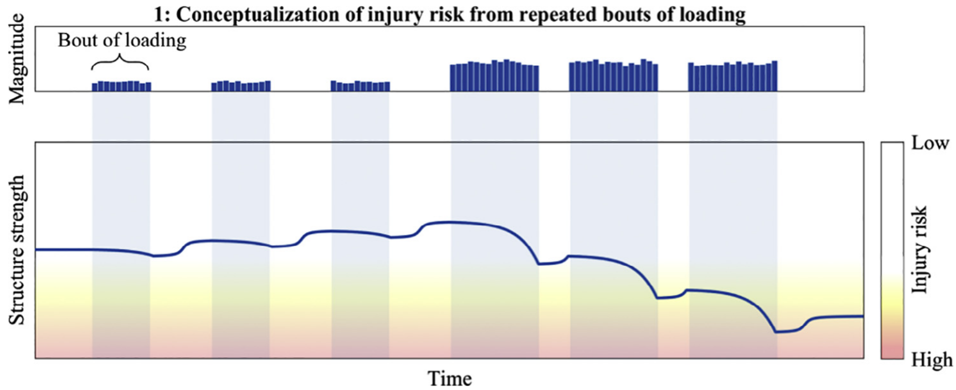

Fig. 1. Conceptual representation of changes in a musculoskeletal structure's strength elicited by the interaction between the number of cycles in a bout of activity, the magnitude of loading in the bout, and the time between bouts. During the first three bouts of loading, the number and magnitude of loading cycles are low and adequate time is allowed for positive remodelling; thus, the structure's strength increases and the likelihood of injury decreases. In contrast, during the last three bouts, the number and magnitude of loading cycles increases and insufficient time between bouts is allowed for positive remodelling; thus, the structure's strength decreases and injury risk increases.

measures for structure loading. As discussed by Miller and Hamill (2009), however, relationships between external and internal loading are complex and non-intuitive due to inter-individual variability in muscle forces and structure morphology. Despite this variability, vGRF is the primary external force acting on runners and it is reasonable to assume that increased external loading translates into increased structure loading. Thus, the mechanisms for RRI can be conceptualized as a combination of vGRFs (load magnitudes) and strides (load cycles) that cause microtrauma to a musculoskeletal structure, with insufficient time for recovery between runs (bouts of loading) (Johnson, 1983; Lysholm & Wiklander, 1987; Renstrom, 1993; Hreljac, 2004; Nielsen et al., 2012).

In spite of this theoretical rationale and much high-quality research, findings relating vGRF and RRI are inconsistent (e.g., Zadpoor and Nikooyan, 2011; van der Worp et al., 2016). This inconsistency may be due in part to previous research largely focusing on relationships between RRI and load magnitudes determined from single representative stances or strides observed in laboratory settings (Miller et al., 2013; Firminger & Edwards, 2016). Such research is constrained in several ways: (1) loading data obtained in laboratories may not accurately represent loading in the field (Andriacchi and Alexander, 2000); (2) loading may change throughout a repetitive task; for example, fatigue can alter biomechanics across a long, exhausting run (Miller et al., 2007; Meardon et al., 2011); and (3) given the importance of repetitive loading in overuse injury, metrics based on a single representative stride tell an incomplete story and are likely insufficient to predict RRI (James et al., 1978; Burr, 1997; Hreljac et al., 2000; Hreljac, 2004; Firminger & Edwards, 2016). Therefore, extrapolation of lab-based, single-stride results may not realistically represent the number or magnitude of loads actually experienced by runners.

Several approaches have been developed to expand on single-stride metrics. Edwards et al. (2010) proposed a '*stressed-life*' method in which the probability of positive and negative remodelling, and consequent tibial stress fracture risk, were estimated as a function of bone strain, number of strides, and structure adaptation. Although extremely useful in elucidating the role that repeated loading plays in RRI, modeling demands and assumptions limit this approach. More easily applied '*per-unit-distance*' and '*cumulative loading*' metrics integrate waveform magnitudes within a stance to calculate load, then sum integrals across loading cycles (Miller et al., 2013, 2014; Petersen et al., 2015; Firminger and Edwards, 2016; Baggaley and Edwards, 2017; Miller, 2017). Findings from these studies have shown potentially non-intuitive results not predicted by single-stride metrics. For example, although reducing stride length decreased ankle joint loading during a single stance, across a 5 km run it *increased* cumulative loading (Firminger & Edwards, 2016). Thus, in agreement with theory, these novel approaches highlight the importance of broadening the focus from single-stride metrics to include repetitive loading in RRI research.

Wearable activity monitors provide the opportunity to broaden the focus from lab-based single-stride metrics. These devices may be capable of non-invasively capturing loading profiles (load magnitude-number combinations) throughout entire runs in the field. For instance, to obtain ecologically valid estimates of peak vGRFs outside the lab, Neugebauer et al. (2012, 2014) simultaneously collected accelerations from hip-mounted activity monitors and GRFs from force plates. With a hold back procedure, one group of participants was used to develop a multiple linear regression relating peak vertical acceleration, mass, and type of locomotion (walk/run) to log-transformed peak vGRF. A second group of participants was used to validate that this equation estimated peak vGRFs within 8.3 ± 3.7% of force plate-measured values (mean ± S D) (Fig. 2A). Other research groups have successfully used activity monitors to measure temporal parameters during running (e.g., Weyand et al., 2001; Auvinet et al., 2002; Wixted et al., 2010; Bergamini et al., 2012; Buchheit et al., 2015). For example, using a sacrum-mounted activity monitor, Lee et al. (2010) measured stride, step, and stance times during running with biases $\leq$1 ms (Fig. 2B).

Here, we combined accelerometer-based methods developed to estimate stride parameters (Lee et al., 2010) and peak vGRF (Neugebauer et al., 2014) and quantified loading profiles throughout entire runs of elite track athletes. We quantified both traditional metrics (number of strides, peak vGRF magnitudes) and a cumulative loading metric and evaluated their relationships to RRI. We hypothesized that runners exhibiting large cumulative loading based on combinations of high peak vGRF and/or high numbers of strides were more likely to develop RRI.

2. Methods

2.1. Participants

Ten National Collegiate Athletic Association Division I runners competing in distance events were recruited from the University of California Davis Men's Track Team. One participant was excluded from analyses due to non-compliance, resulting in a final

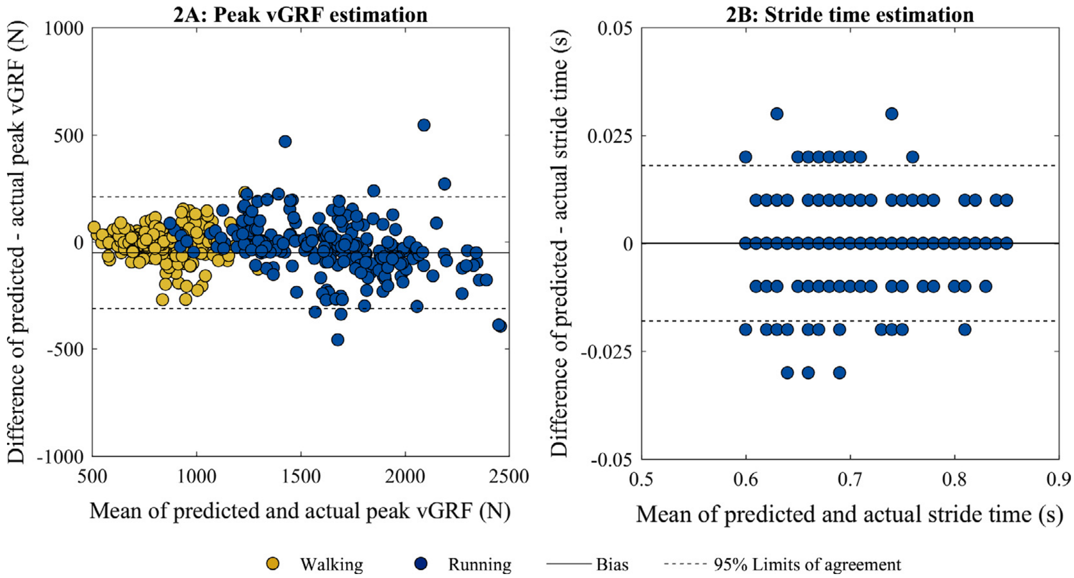

Fig. 2. Illustration of the difference between actual values and those predicted with accelerometer-based estimations. (A) Peak vGRF was estimated using multiple linear regression with factors of peak vertical acceleration, mass, and type of locomotion (walk/run). The regression equation estimated peak vGRFs within 8.3 ± 3.7% of force plate-measured values (mean ± SD) (Neugebauer et al., 2014). (B) Sacrum accelerations were used to estimate stride times with biases <1 ms when compared to motion capture (adapted with permission, Lee et al., 2010, adapted with permission).

sample of nine (Table 1). Participants were excluded if they suffered a major injury within the past 12 months (physician diagnosed injury preventing training for $\geq$2 months) or a minor injury with a return-to-training less than six weeks before the study (trainer or self-diagnosed injury preventing training for $\geq$1 month). The University of California Davis Institutional Review Board approved all procedures and participants provided written informed consent.

2.2. Training prescriptions

Data were collected during training runs over a 60-day period during the Track and Field season. Coaches provided schedules prescribing daily training for individual participants. Running prescriptions for each training session were coded based on prescribed training time and optional training time (scale variables), whether the training was middle- or long-distance, self-supervised, contained high intensity portions (e.g., sprints), included a pre-race routine, and/or included any otherwise undescribed training (categorical variables).

2.3. Training questionnaires

After each training session, participants rated their overall pain/fatigue (Table 2), reported whether they completed the prescribed training session, and, if they did not, described the reason. If failure to complete training was due to RRI, participants provided details on injury location and severity.

Table 2
Pain/fatigue scale. After each training session, participants rated overall musculoskeletal pain/fatigue on a scale of integers from 1 to 9.

Quantitative rating	Qualitative description
1	No pain or fatigue. *Your muscles/bones feel as though they are at optimal training levels*
3	Minimal pain or fatigue. *You feel slightly less than optimal, but you still feel as though you can complete a rigorous work out*
5	Moderate pain or fatigue. *You have noticeable pain/fatigue in your muscles/bones, but feel as though you could complete an average workout*
7	High pain or fatigue. *You have a significant level of pain/fatigue and feel as though you would have difficulty completing an average workout*
9	Extreme pain or fatigue. *You have extreme pain/fatigue in your muscles/bones and do not feel as though you could complete a workout*

2.4. Accelerometer data

Each participant was assigned an activity monitor with a tri-axial linear accelerometer (Fig. 3A) (ADXL345, Analog Devices, Norwood, MA; ±8 g; 48.4–52.4 Hz, twice the frequency observed in vGRFs during running; Kiernan et al., 2017). Participants were instructed on activity monitor use and wear. Before each training session, participants fixed the monitor to their lateral right iliac crest with a neoprene belt and turned it on (Fig. 3B and C). Participants wore the monitor throughout the entire training session, turning it off and automatically generating a time-stamped data file after the session was complete. Each week, researchers collected data and ensured monitor function.

Table 1
Participant characteristics (mean ± SD). Injured participants were significantly older than uninjured participants (* p = 0.02) but were otherwise statistically similar (ps > 0.05).

	n	Age (years)*	Weight (N)	Height (cm)
All participants	9	18.7 ± 1.0	629.37 ± 71.35	178.4 ± 4.6
Uninjured participants	6	18.2 ± 0.4	599.23 ± 64.0	178.3 ± 4.1
Injured participants	3	19.7 ± 1.2	689.64 ± 44.15	178.6 ± 6.4

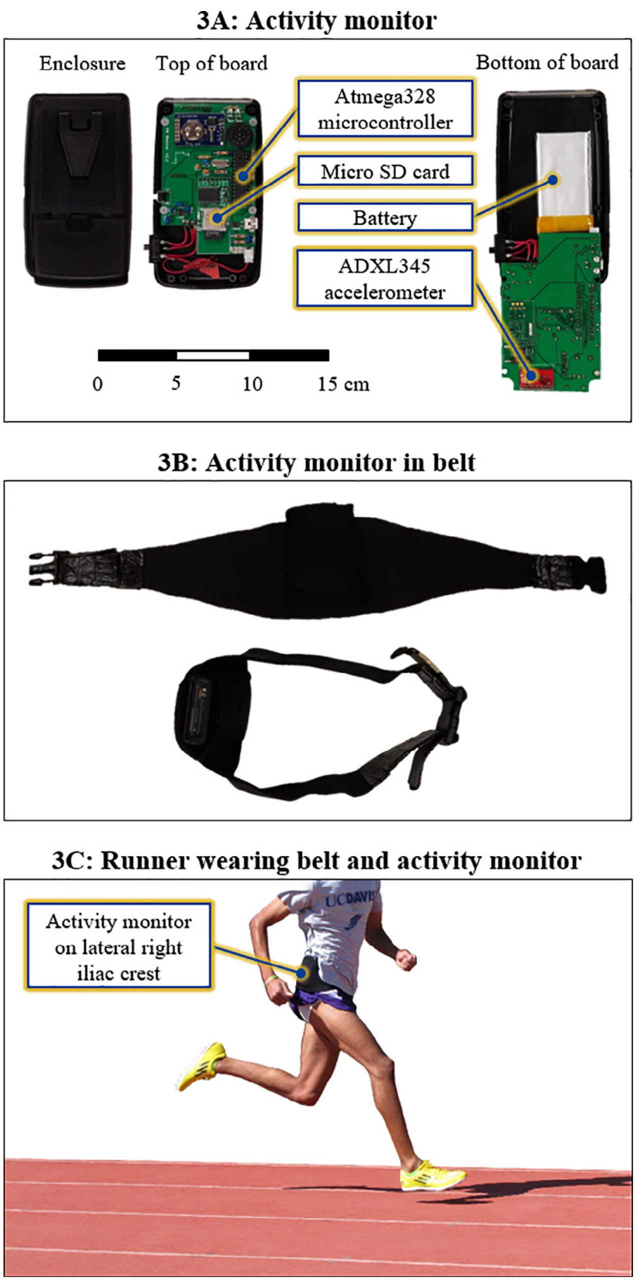

Fig. 3. Illustration of the approach used to quantify hip acceleration. The activity monitor including accelerometer, battery, microcontroller, and memory card (A) was placed in a neoprene belt (B) and secured to the runner's lateral right iliac crest (C).

Custom MATLAB scripts (R2016a, The MathWorks, Natick, MA) were used to extract unfiltered accelerometer data. The DC component was calculated during a 30 s static period and subtracted from the signal, and monitor-specific calibrations were applied, yielding output in "gs" relative to a reference frame aligned with the activity monitor housing and participant (Coolbaugh and Hawkins, 2014). The anterior-posterior axis was used to identify right and left foot strikes (Lee et al., 2010). Left stances (contralateral to the monitor) were discarded. Peak vertical accelerations during right stances were extracted and entered into a regression equation to estimate right stance peak vGRF (Neugebauer et al., 2014). Data were collected throughout an entire training session and could include warm up drills, stretching, breaks in running to wait at traffic lights, etc. Thus, published stride times and peak vGRF magnitudes were used to eliminate data ±3 SD outside the ranges expected for running (Cavanagh and Lafortune, 1980; Munro et al., 1987; Cavanagh and Kram, 1989; Williams et al., 1991; De Wit et al., 2000; Weyand et al., 2000; Leskinen et al., 2009; Weyand et al., 2010; Meardon et al., 2011). Periods evincing vGRF magnitudes and stride times within expected ranges but with <10 consecutive strides were also eliminated to ensure participants had achieved steady running speeds and that pattern recognition algorithms were not biased by aberrant waveforms. Periods of running with $\geq$10 strides were concatenated for analysis.

Mean peak vGRF and total number of strides were calculated for each training session. Data were grouped by training prescription and evaluated for outliers exceeding ±2 SD of prescription mean number of strides (e.g., Fig. 4A). High outliers were considered real and complete data but misrepresentative of the prescription (i.e., the participant violated the coach's instructions and ran longer than prescribed); thus, prescription data were removed to avoid biasing imputation (see below; 1.67% of data). Low outliers were considered potentially incomplete data collections (i.e., the accelerometer turned off during data collection); thus, peak vGRF and number of strides were deleted and imputed (see below; 2.15% of data).

2.5. Multiple imputation

A total of 419 training sessions were prescribed, however, item non-response (e.g., the participant forgot to turn on the accelerometer or fill out the questionnaire) or outlier deletion caused the loss of 22.4% of accelerometer and 43.4% of pain/fatigue data. Consistent with recommendations for the use of accelerometers in measuring physical activity (Catellier et al., 2005; Ward et al., 2005), missing data were multiply imputed using prescribed training, participant anthropometrics, and accelerometer variables, and assuming that data were missing at random. Multiple imputation uses associations with observed data to generate multiple plausible values for each missing data point. Each of these multiple plausible data sets is then separately analyzed and analyses are pooled. This procedure minimizes bias and results in valid statistical inferences that reflect the uncertainty due to missing values. Here, 50 imputed data sets were generated with SPSS (v24.0, IBM Corp., Armonk, NY) and pooled for analysis using Rubin's rules (Rubin, 1987). To evaluate imputation accuracy, a second imputation was conducted where known data were deleted from two representative prescriptions. Imputed values for deleted data were not significantly different than original data (evaluated with uncorrected paired t-tests with significance set at $p < 0.05$) (Fig. 4).

2.6. Analyses

After imputation, mean estimated peak vGRF and number of strides per training session were calculated for each participant. Based on the S-N curve of tendon, an 'effective' load for soft-tissue injury was calculated by weighting the peak vGRF to the 9th power (Baggaley & Edwards, 2017). Weighted peak vGRFs were summed across each training session and a mean weighted cumulative load per training session was calculated. Participants were separated into injured (missed training due to self-reported RRI) and uninjured (no missed training due to RRI) groups. Injured and uninjured mean pain/fatigue, mean estimated peak vGRF, mean strides per training session, and mean weighted cumulative loading per training session were entered into independent samples t-tests. Significance was set at $p < 0.05$ and corrected with a False Discovery Rate procedure (Benjamini & Hochberg, 1995).

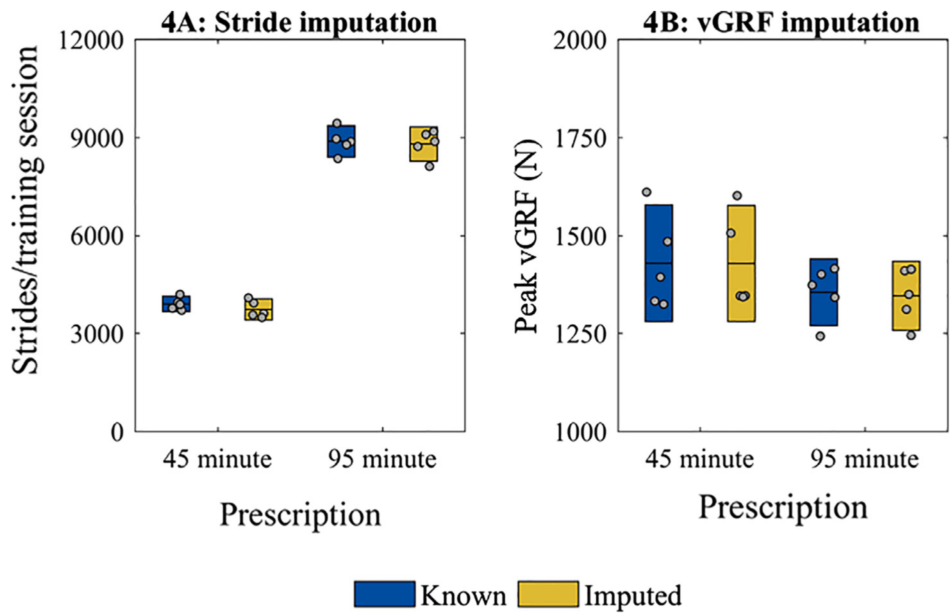

Fig. 4. Comparison of known and imputed data for number of strides and peak vGRF. Mean (black line) and 95% CI (colored bar) of (A) number of strides, and (B) estimated peak vGRF for known and imputed data from two representative training prescriptions: a 95-min training session and a 45-min training session with high intensity portions. Note that consistent with expectations there are (1) no significant differences between known and imputed data, (2) significantly more strides for the longer prescribed training session, and (3) a trend to higher vGRF for the shorter prescribed training session with high intensity portions. Gray dots represent individual data points (training sessions). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Results

3.1. Injury

Across the 60-day study, three participants (33%) lost training time to self-reported foot, adductor, and hamstring soft-tissue RRIs with 7, 10, and 33 training days lost respectively. Injured participants were significantly older than uninjured participants ($p = 0.02$) but did not significantly differ in height or weight (evaluated with uncorrected independent samples t-tests with significance set at $p < 0.05$) (Table 1).

3.2. Pain vs. injury

Injured and uninjured participants did not report significantly different pain/fatigue ($p = 0.56$). This result suggests that high subjective pain/fatigue may not predict impending RRI and highlights the need for additional objective metrics (Fig. 5A; Fig. 6A).

3.3. Biomechanics vs. injury

Mean number of strides per training session did not differ between injured and uninjured participants ($p = 0.91$) (Fig. 5B). Injured participants did, however, have significantly greater mean estimated peak vGRF ($p = 0.01$) (Fig. 5C) and mean weighted cumulative loading per training session ($p < 0.01$) (Fig. 5D). Injured runners also appeared as outliers when plotted on a mean estimated peak vGRF vs. mean strides per training session graph, suggesting greater injury risk at combinations of high loads and magnitudes (Fig. 6A). Participant's chance of injury across two months was coded as 1 for injured and 0 for uninjured then interpolated across a generalizable range of peak vGRF and stride number combinations. This process resulted in a contour pattern similar to the curves of Davis'/Wolfe's Laws (1867/1892) (Fig. 6B), illustrating that the risk of injury increases when high load magnitudes are repeatedly applied.

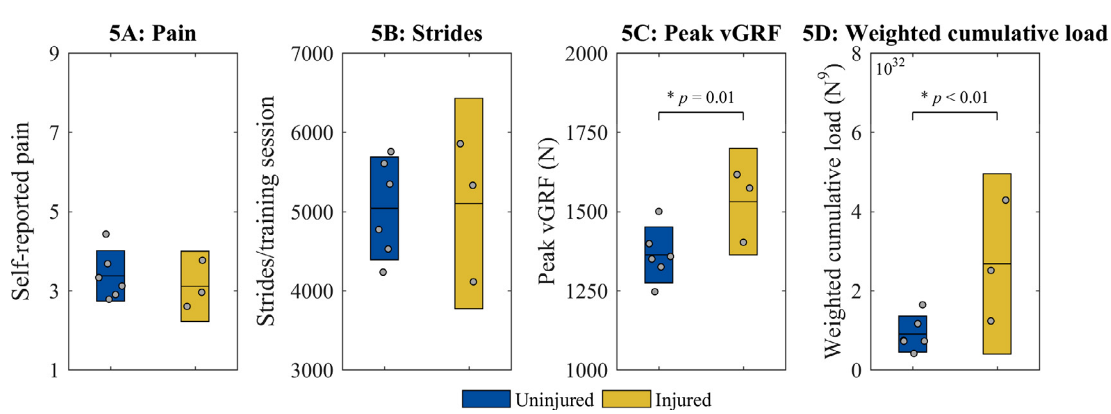

Fig. 5. Outcome metrics for injured and uninjured runners. Mean (black line) and 95% CI (colored bar) of (A) pain, (B) mean number of strides per training session, (C) mean estimated peak vGRF, and (D) mean weighted cumulative load (sum of estimated peak vGRF weighted to the ninth power) per training session. Gray dots represent individual data points (participant means).

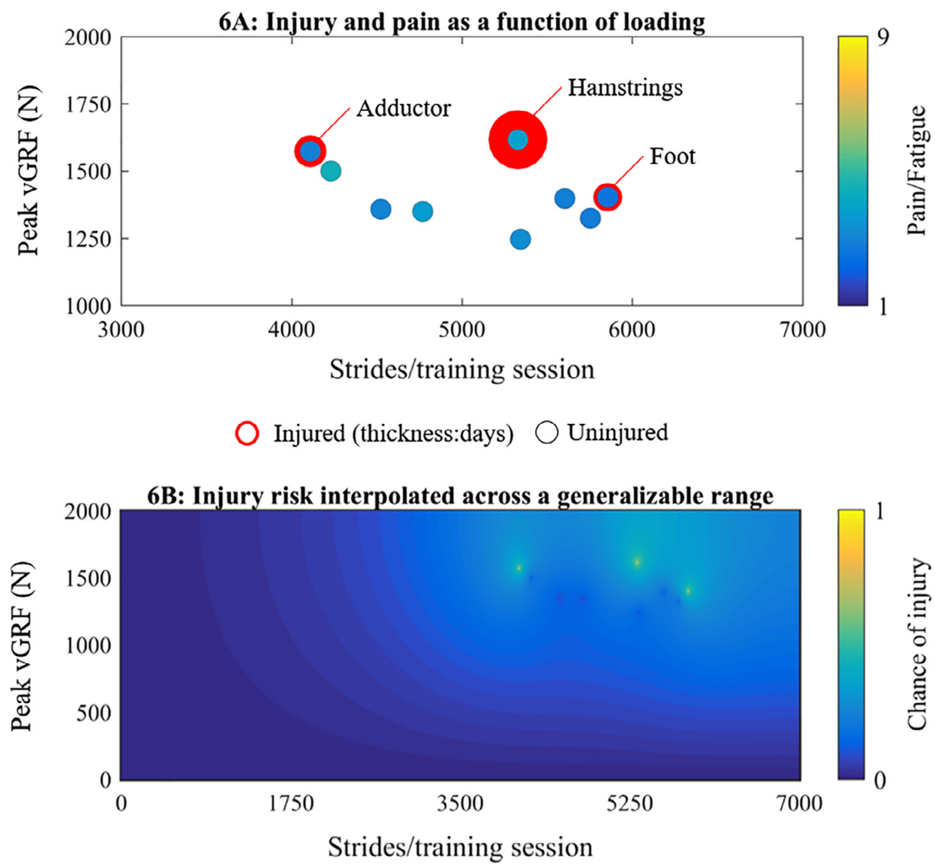

Fig. 6. Relationships between loading profiles, pain, and injury. (A) Each participant's mean estimated peak vGRF vs. strides per training session. Color represents mean reported pain/fatigue. Thickness of encircling red line represents time lost due to injury (if any). (B) Empirical data coded as 0 for uninjured and 1 for injured and interpolated to conceptualize injury risk across a generalizable range of peak vGRF and strides/training session. Color represents chance of injury over two-months on a scale from 0 (not predicted to incur injury) to 1 (predicted to incur injury).

4. Discussion

In this study we used wearable activity monitors to prospectively measure runners' loading profiles in the field. We found that injured runners had higher estimated peak vGRFs and weighted cumulative loads than uninjured runners. To our knowledge this is the first study to (1) apply accelerometer-based estimates of peak vGRF and stride number to RRI prediction in a prospective sample, and (2) empirically validate cumulative loading metrics in RRI prediction. These novel results suggest that the accelerometer-based models used here are capable of capturing inter-participant differences in loading profiles that may be predictive of RRI. These findings support both popular and emerging theories in RRI research: namely, that high vGRF magnitudes may be a contributing factor in RRI as speculated by Cavanagh and Lafortune (1980) and others, and that cumulative loading metrics may be a valid index of RRI risk (e.g., Petersen et al., 2015). Further, the methods used here show promise in identifying safe limits of loading that could allow coaches and athletes to develop and adapt training prescriptions based on individual athlete loading profiles.

The development of objective metrics similar to those presented here appears critical given the high incidence of RRI (van Gent et al., 2007; Lopes et al., 2012; Videbæk et al., 2015) and apparent disconnect between subjective pain/fatigue and RRI. Although pain has been used to define RRI elsewhere, when RRI is instead defined as training time lost, these variables appear to represent separate constructs. Indeed, time lost appears to be a much more conservative definition of injury (Bahr, 2009; Buist et al., 2010; Clarsen et al., 2013; Clarsen and Bahr, 2014), does not appear related to pain across various RRIs (Hespanhol Junior et al., 2013), and does not evince the same statistical relationships with other variables as pain (Kiernan et al., 2015, 2016). Similarly, the present finding that injured runners did not report higher pain/fatigue, suggests that runners may be insensitive to impending injury. Indeed, it should be noted that injured runners actually tended to report *lower* pain than uninjured runners (mean 3.4 uninjured vs. 3.1 injured). Given the limited power in the present analysis and the risk of Type II error, however, we cannot rule out that sensitivity to pain may be protective, allowing runners to adapt motor patterns and avoid injury. In any case, subjective pain alone appears insufficient to predict time-loss injuries, highlighting both the important role that providing biomechanics-based feedback about RRI risk could play and the importance of discretely reporting injury as operationalized by medical, time-loss, and pain definitions to facilitate comparison across studies (Fuller et al., 2006).

The activity monitor-derived objective metrics used here address several constraints in current biomechanics research. In the past, biomechanics research has largely been restricted to lab and clinical settings. This restriction has undermined the ecological validity of findings given lab-based observations may not be generalizable to real world behavior (Andriacchi and Alexander, 2000). Further, the constraints of the lab have prevented accurate measurement of the number of loads actually experienced by runners – a variable theorized to play a critical role in RRI causation (Nielsen et al., 2012; Bertelsen et al., 2017). The current results join an emerging body of literature (e.g., Coolbaugh et al., 2015; Cain et al., 2016; Willy et al., 2016; Gruber et al., 2017; Ruder et al.,

2017) that demonstrates the role activity monitor-based methods may play in overcoming previous constraints and collecting large ecologically valid data sets.

The results presented here were largely consistent with our hypotheses; however, the number of strides per training session did not significantly differ between injured and uninjured participants. Participants in the present study were elite athletes with training regimes highly constrained by coach's prescriptions. Thus, all participants ran for similar amounts of time and there was relatively little inter-participant variability in the number of strides. It seems likely that in an unconstrained population, such as recreational runners, the number of strides completed in each training session would vary greatly; in which case, the number of strides might play a larger role in RRI. Further research with more heterogeneous samples is required to more fully investigate the role of stride number and cumulative loading in RRI.

The homogeneity of the present sample was, however, beneficial in constraining the time between training sessions. As outlined in the introduction, repeated bouts of loading play a key role in RRI causation, since adequate time is required between bouts for positive remodelling of injury-prone structures (Fig. 1). In spite of this key role, the present analyses focus on metrics across a mean training session, largely ignoring the role of repeated bouts of loading. We feel this decision is justified given the highly constrained training prescriptions in our sample: injured and uninjured participants trained 85.8% and 85.6% of potential days respectively, and times between training sessions were extremely similar. Thus, variability in the number of, and time between, bouts likely has little impact on the present results, and taking means across training sessions captures critical differences. In a more variable sample, however, it seems likely that the time between bouts could play a large role in RRI. This role could be captured either by identifying critical time periods over which load accumulates to cause RRI (e.g., the ratio of workload across one week relative to workload across four weeks predicts non-contact injury; Blanch and Gabbett, 2016; though this method is controversial; cf. Lolli et al., 2017), by calculating a daily probability of injury in a given structure based on the probability of positive and negative remodeling as a function of estimated structure loading, number of strides, and structure adaptation (e.g., Edwards et al., 2010), or by applying Miner's Rule to calculate cumulative damage (e.g., Miller, 2017). Enacting these potential methods requires further research to determine mathematical associations between external loading conditions, internal structure loading, microtrauma accumulation, the temporal healing response, and RRI.

The present investigation represents a preliminary proof-of-concept application of novel methods. Although we observed promising results, there are a number of methodological refinements that could improve the techniques used here. For example, some evidence suggests the magnitude and/or rate of loading associated with the *first* peak of the vGRF waveform is more predictive of RRI relative to the magnitude of the *second* peak (e.g., Zadpoor & Nikooyan, 2011; van der Worp et al., 2016; cf. Grimston et al., 1991; Messier et al., 1991; Ferber et al., 2002). The method used here is unable to discriminate between the two peaks; rather, *absolute* peak acceleration is used to estimate *absolute* peak vGRF. Further, previous studies quantifying cumulative loading have summed waveforms integrated across stance (Miller et al., 2013, 2014; Petersen et al., 2015; Firminger and Edwards, 2016; Baggaley and Edwards, 2017; Miller, 2017). Methodological limitations prevented the use of an integral in the current study; instead, we summed peak vGRFs. Though this method captures information about the number and maximum magnitude of loads, potentially important information about loading throughout the entire gait cycle and/or the load duration is lost. Finally, given the preponderance of unilateral RRIs (Lopes et al., 2012) and the potential role bilateral asymmetries play in RRI (e.g., Zifchok et al., 2006), methods to calculate loading and RRI separately for each limb should be developed. These, and other, methodological improvements should be considered as the field of activity monitor-based biomechanics develops.

In sum, we observed significantly different loading profiles between injured and uninjured track runners across a 60-day prospective period. These promising preliminary results provide evidence that further work in this area is warranted. Follow up studies should build on the current methods and collect data from larger, more heterogeneous, samples. Calculating critical time periods over which load accumulates to cause injury and/or calculating rolling probabilities of injury based on loading may lead to the development of thresholds for RRI based on athlete-specific loading histories. Such results would help refine injury prediction models and provide the evidence necessary to develop adaptive feedback and training prescriptions that account for the mechanics and loading profiles of individual runners.

Conflict of interest statement

None of the authors have potential conflicts of interest or will gain financially from the results of the study.

Acknowledgements

Thanks to Coach Drew Wartenburg and the UC Davis Men's NCAA Track and Field team for their participation, and to Henry Luk, Amar Dholakia, and Shonit Sharma for contributions to earlier work. DK was supported by a scholarship from the Natural Sciences and Engineering Research Council of Canada. CLC was supported by an Achievement Rewards for College Scientists (ARCS) scholarship. MACM and MM were supported by the UC Davis College of Biological Sciences Dean's Mentorship Award. Supporting agencies had no involvement in the design, collection, or interpretation of this study.

References

Andriacchi, T.P., Alexander, E.J., 2000. Studies of human locomotion: past, present and future. J. Biomech. 33, 1217–1224.

Auvinet, B., Gloria, E., Renault, G., Barrey, E., 2002. Runner's stride analysis: comparison of kinematic and kinetic analyses under field conditions. Sci. Sports 17 (2), 92–94.

Baggaley, M., Edwards, W.B., 2017. Effect of running speed on Achilles tendon injury potential: use of a weighted impulse measure. Med. Sci. Sports Exercise 49 (5S), 139.

Bahr, R., 2009. No injuries, but plenty of pain? On the methodology for recording overuse symptoms in sports. Br. J. Sports Med. 43 (13), 966–972.

Benjamini, Y., Hochberg, Y., 1995. Controlling the false discovery rate: a practical and powerful approach to multiple testing. J. R. Stat. Soc. Ser. B (Methodol.) 57 (1), 289–300.

Bertelsen, M.L., Hulme, A., Petersen, J., Brund, R.K., Sørensen, H., Finch, C.F., Parner, E.T., Nielsen, R.O., 2017. A framework for the etiology of running-related injuries. Scand. J. Med. Sci. Sports 27 (11), 1170–1180.

Bergamini, E., Picerno, P., Pillet, H., Natta, F., Thoreux, P., Camomilla, V., 2012. Estimation of temporal parameters during sprint running using a trunk-mounted inertial measurement unit. J. Biomech. 45 (6), 1123–1126.

Blanch, P., Gabbett, T.J., 2016. Has the athlete trained enough to return to play safely? The acute: chronic workload ratio permits clinicians to quantify a player's risk of subsequent injury. Br. J. Sports Med. 50 (8), 471–475.

Buchheit, M., Gray, A., Morin, J., 2015. Assessing stride variables and vertical stiffness with GPS embedded accelerometers: preliminary insights for the monitoring of neuromuscular fatigue on the field. J. Sports Sci. Med. 14, 698–701.

Buist, I., Bredeweg, S.W., Bessem, B., van Mechelen, W., Lemmink, K.A.P.M., Diercks, R.L., 2010. Incidence and risk factors of running-related injuries during preparation for a 4-mile recreational running event. Br. J. Sports Med. 44, 598–604.

Burr, D.B., 1997. Bone, exercise, and stress fractures. Exercise Sport Sci. Rev. 25 (1), 171–194.

Burr, D.B., Robling, A.G., Turner, C.H., 2002. Effects of biomechanical stress on bones in animals. Bone 30 (5), 781–786.

Cain, S.M., McGinnis, R.S., Davidson, S.P., Vitali, R.V., Perkins, N.C., McLean, S.G., 2016. Quantifying performance and effects of load carriage during a challenging balancing task using an array of wireless inertial sensors. Gait and Posture 43 (Suppl C), 65–69.

Carter, D.R., Caler, W.E., 1985. A cumulative damage model for bone fracture. J Orthopaedic Res 3 (1), 84–90.

Catellier, D.J., Hannan, P.J., Murray, D.M., Addy, C.L., Conway, T.L., Yang, S., Rice, J.C., 2005. Imputation of missing data when measuring physical activity by accelerometry. Med. Sci. Sports Exercise 37 (11 Suppl), S555–S562.

Cavanagh, P.R., Kram, R., 1989. Stride length in distance running: velocity, body dimensions, and added mass effects. Med. Sci. Sports Exercise 21 (4), 467–479.

Cavanagh, P.R., Lafortune, M.A., 1980. Ground reaction forces in distance running. J. Biomech. 13, 397–406.

Clarsen, B., Bahr, R., 2014. Matching the choice of injury/illness definition to study setting, purpose and design: one size does not fit all! Br. J. Sports Med. 48 (7), 510–512.

Clarsen, B., Myklebust, G., Bahr, R., 2013. Development and validation of a new method for the registration of overuse injuries in sports injury epidemiology: the Oslo Sports Trauma Research Centre (OSTRC) Overuse Injury Questionnaire. Br. J. Sports Med. 47 (8), 495–502.

Coolbaugh, C.L., Hawkins, D.A., 2014. Standardizing accelerometer-based activity monitor calibration and output reporting. J. Appl. Biomech. 30 (4), 594–597.

Coolbaugh, C.L., Raymond, S.C.J., Hawkins, D.A., 2015. Feasibility of a dynamic web guidance approach for personalized physical activity prescription based on daily information from wearable technology. J. Med. Int. Res.: Res. Protocols 4 (2), e67.

Davis, H.G., 1867. Conservative Surgery. D. Appleton & Co., New York, NY.

De Wit, B., De Clercq, D., Aerts, P., 2000. Biomechanical analysis of the stance phase during barefoot and shod running. J. Biomech. 33 (3), 269–278.

Edwards, W.B., Taylor, D., Rudolphi, T.J., Gillette, J.C., Derrick, T.R., 2009. Effects of stride length and running mileage on a probabilistic stress fracture model. Med. Sci. Sports Exercise 41 (12), 2177–2184.

Edwards, W.B., Taylor, D., Rudolphi, T.J., Gillette, J.C., Derrick, T.R., 2010. Effects of running speed on a probabilistic stress fracture model. Clin. Biomech. 25 (4), 372–377.

Ferber, R., McClay-Davis, I., Hamill, J., Pollard, C.D., McKeown, K.A., 2002. Kinetic variables in subjects with previous lower extremity stress fractures. Med. Sci. Sports Exercise 34, S5.

Firminger, C.R., Edwards, W.B., 2016. The influence of minimalist footwear and stride length reduction on lower-extremity running mechanics and cumulative loading. J. Sci. Med. Sport 19 (12), 975–979.

Fuller, C.W. et al., 2006. Consensus statement on injury definitions and data collection procedures in studies of football (soccer) injuries. Scand. J. Med. Sci. Sports 16 (2), 83–92.

Frost, H.M., 1998. A brief review for orthopedic surgeons: fatigue damage (microdamage) in bone (its determinants and clinical implications). Journal of Orthopaedic Science 3 (5), 272–281.

Grimston, S.K., Engsberg, J.R., Kloiber, R., Hanley, D.A., 1991. Bone mass, external loads, and stress fracture in female runners. Int. J. Sport Biomech. 7 (3), 293–302.

Gruber, A.H., Paquette, M.R., Camelio, K., Powell, D.W., Vollmar, J.E., 2017. Multiscale entropy of center of mass acceleration as a measure for cumulative running fatigue. In: Proceedings of the 41st American Society of Biomechanics. Boulder, CO.

Hespanhol Junior, L.C., Pena Costa, L.O., Lopes, A.D., 2013. Previous injuries and some training characteristics predict running-related injuries in recreational runners: a prospective cohort study. J. Physiother. 59 (4), 263–269.

Hespanhol Junior, L.C., van Mechelen, W., Postuma, E., Verhagen, E., 2016. Health and economic burden of running-related injuries in runners training for an event: a prospective cohort study. Scand. J. Med. Sci. Sports 26 (9), 1091–1099.

Hreljac, A., Marshall, R.N., Hume, P.A., 2000. Evaluation of lower extremity overuse injury potential in runners. Med. Sci. Sports Exercise 32 (9), 1635–1641.

Hreljac, A., 2004. Impact and overuse injuries in runners. Med. Sci. Sports Exercise 36 (5), 845–849.

James, S.L., Bates, B.T., Osternig, C.R., 1978. Injuries to runners. Am. J. Sports Med. 6, 40–50.

Johnson, R., 1983. Common running injuries of the leg and foot. Minnesota Med. 66 (7), 441–444.

Kiernan, D., Krupenevich, R., Shim, J.K., Miller, R.H., 2016. Baseline correlates of running injury: hip hypermobility but not lower limb strength relates to future running injury. Med. Sci. Sports Exercise 48 (5), 170.

Kiernan, D., Miller, R.H., Baum, B.S., Kwon, H.J., Shim, J.K., 2017. Amputee locomotion: frequency content of prosthetic vs. intact limb vertical ground reaction forces during running and the effects of filter cut-off frequency. J. Biomech. 60, 248–252.

Kiernan, D., Shim, J.K., Miller, R.H., 2015. Vertical ground reaction force magnitudes and rates not positively correlated with prospective running injury. In: Proceedings of the 39th American Society of Biomechanics. Columbus, OH.

Lee, J.B., Mellifont, R.B., Burkett, B.J., 2010. The use of a single inertial sensor to identify stride, step, and stance durations of running gait. J. Sci. Med. Sport 13 (2), 270–273.

Leskinen, A., Häkkinen, K., Virmavirta, M., Isolehto, J., Kyröläinen, H., 2009. Comparison of running kinematics between elite and national-standard 1500-m runners. Sports Biomech. 8 (1), 1–9.

Lolli, L., Batterham, A.M., Hawkins, R., Kelly, D.M., Strudwick, A.J., Thorpe, R., Gregson, W., Atkinson, G., 2017. Mathematical coupling causes spurious correlation within the conventional acute-to-chronic workload ratio calculations. British Journal of Sports Medicine; Available online: 3 Nov 2017.

Lopes, A.D., Hespanhol Júnior, L.C., Yeung, S.S., Costa, L.O.P., 2012. What are the main running-related musculoskeletal injuries? A systematic review. Sports Med. 42 (10), 891–905.

Lysholm, J., Wiklander, J., 1987. Injuries in runners. Am. J. Sports Med. 15 (2), 168–171.

Meardon, S.A., Hamill, J., Derrick, T.R., 2011. Running injury and stride time variability over a prolonged run. Gait Posture 33 (1), 36–40.

Messier, S.P., Davis, S.E., Curl, W.W., Lowery, R.B., Pack, R.J., 1991. Etiologic factors associated with patellofemoral pain in runners. Med. Sci. Sports Exercise 23 (9), 1008–1015.

Miller, R.H., Hamill, J., 2009. Computer simulation of the effects of shoe cushioning on internal and external loading during running impacts. Comput. Methods Biomech. Biomed. Eng. 12 (4), 481–490.

Miller, R.H., 2017. Joint loading in runners does not initiate knee osteoarthritis. Exercise Sport Sci. Rev. 45 (2), 87–95.

Miller, R.H., Edwards, W.B., Deluzio, K.J., 2014. Energy expended and knee joint load accumulated when walking, running, or standing for the same amount of time. Gait Posture 41 (1), 9–11.

Miller, R.H., Edwards, W.B., Brandon, S.C.E., Morton, A.M., Deluzio, K.J., 2013. Why don't most runners get knee osteoarthritis? A case for per-unit-distance loads. Med. Sci. Sports Exercise 46 (3), 572–579.

Miller, R.H., Lowry, J.L., Meardon, S., Gillette, J.C., 2007. Lower extremity mechanics of iliotibial band syndrome during an exhaustive run. Gait Posture 26 (3), 407–413.

Munro, C.F., Miller, D.I., Fuglevand, A.J., 1987. Ground reaction forces in running: a reexamination. J. Biomech. 20 (2), 147–155.

Neugebauer, J.M., Collins, K.H., Hawkins, D.A., 2014. Ground reaction force estimates from ActiGraph GT3X+ hip accelerations. PLoS ONE 9 (6), e99023.

Neugebauer, J.M., Hawkins, D.A., Beckett, L., 2012. Estimating youth locomotion ground reaction forces using an accelerometer-based activity monitor. PLoS ONE 7 (10), e48182.

Nielsen, R.O., Buist, I., Sørensen, H., Lind, M., Rasmussen, S., 2012. Training errors and running related injuries: a systematic review. Int. J. Sports Phys. Ther. 7 (1), 58–75.

Petersen, J., Sorensen, H., Nielsen, R.O., 2015. Cumulative loads increase at the knee joint with slow-speed running compared to faster running: a biomechanical study. J. Orthopaedic Sports Phys. Therapy 45 (4), 316–322.

Renstrom, A.F., 1993. Mechanism, diagnosis, and treatment of running injuries. Instruct. Course Lectures 42, 225–234.

Rolf, C., 1995. Overuse injuries of the lower extremity in runners. Scand. J. Med. Sci. Sports 5 (4), 181–190.

Rubin, D.B., 1987. Multiple Imputation for Nonresponse in Surveys. John Wiley & Sons, Hoboken, N.J..

Ruder, M., Jamison, S.T., Tenfore, A., Hannan, M., Davis, I., 2017. Relationship of footstrike pattern and landing impacts during a marathon race. Med. Sci. Sports Exercise 49 (5), 136.

Shepherd, J.H., Screen, H.R.C., 2013. Fatigue loading of tendon. Int. J. Exp. Pathol. 94 (4), 260–270.

The Outdoor Foundation, 2016. Outdoor Participation Report 2016. Retrieved from: <http://www.outdoorfoundation.org/pdf/ResearchParticipation2016.pdf>.

van der Worp, H., Vrielink, J.W., Bredeweg, S.W., 2016. Do runners who suffer injuries have higher vertical ground reaction forces than those who remain injury-free? A systematic review and meta-analysis. Br. J. Sports Med. 50 (8), 450–457.

van Gent, R.N., Siem, D., van Middelkoop, M., van Os, A.G., Bierma-Zeinstra, S.M.A., Koes, B.W., 2007. Incidence and determinants of lower extremity running injuries in long distance runners: a systematic review. Br. J. Sports Med. 41 (8), 469–480.

Videbæk, S., Bueno, A.M., Nielsen, R.O., Rasmussen, S., 2015. Incidence of running-related injuries per 1000 h of running in different types of runners: a systematic review and meta-analysis. Sports Med. 45 (7), 1017–1026.

Ward, D.S., Evenson, K.R., Vaughn, A., Rodgers, A.B., Troiano, R.P., 2005. Accelerometer use in physical activity: Best practices and research recommendations. Med. Sci. Sports Exercise 37 (11 Suppl), S582–S588.

Weightman, B., Chappell, D.J., Jenkins, E.A., 1978. A second study of tensile fatigue properties of human articular cartilage. Ann. Rheumatic Diseases 37 (1), 58–63.

Weyand, P.G., Sternlight, D.B., Bellizzi, M.J., Wright, S., 2000. Faster top running speeds are achieved with greater ground forces not more rapid leg movements. J. Appl. Physiol. 89 (5), 1991–1999.

Weyand, P.G. et al., 2001. Ambulatory estimates of maximal aerobic power from foot-ground contact times and heart rates in running humans. J. Appl. Physiol. 91 (1), 451–458.

Weyand, P.G., Sandell, R.F., Prime, D.N.L., Bundle, M.W., 2010. The biological limits to running speed are imposed from the ground up. J. Appl. Physiol. 108 (4), 950–961.

Williams, K.R., Snow, R., Agruss, C., 1991. Changes in distance running kinematics with fatigue. Int. J. Sport Biomech. 7, 138–162.

Willy, R.W., Buchenic, L., Rogacki, K., Ackerman, J., Schmidt, A., Willson, J.D., 2016. In-field gait retraining and mobile monitoring to address running biomechanics associated with tibial stress fracture. Scand. J. Med. Sci. Sports 26 (2), 197–205.

Wixted, A.J., Billing, D.C., James, D.A., 2010. Validation of trunk mounted inertial sensors for analysing running biomechanics under field conditions, using synchronously collected foot contact data. Sports Eng. 12 (4), 207–212.

Wolff, J., 1892. The law of bone remodelling. Translation of Das Gesetz der Transformation der Knochen by Maquet, P.G.J., Furlong, R., 1986. Springer-Verlag, Berlin.
Wren, T.A., Lindsey, D.P., Beaupre, G.S., Carter, D.R., 2003. Effects of creep and cyclic loading on the mechanical properties and failure of human Achilles tendons. Ann. Biomed. Eng. 31 (6), 710–717.
Zadpoor, A.A., Nikooyan, A.A., 2011. The relationship between lower-extremity stress fractures and the ground reaction force: a systematic review. Clin. Biomech. 26 (1), 23–28.
Zifchok, R.A., Davis, I., Hamill, J., 2006. Kinetic asymmetry in female runners with and without retrospective tibial stress fractures. J. Biomech. 39 (15), 2792–2797.