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Using wearable technology data to explain recreational running injury: A prospective longitudinal feasibility study

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A R T I C L E I N F O

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A B S T R A C T

Objectives: Investigate 1) if collecting and analysing wristwatch inertial measurement unit (IMU) and global positioning system (GPS) data using a commercially-available training platform was feasible in recreational runners and 2) which variables were associated with subsequent injury.
Design: Prospective longitudinal cohort.
Participants: Healthy recreational runners.
Main outcome measures: We set *a priori* feasibility thresholds for recruitment (maximum six-months), acceptance (minimum 80%), adherence (minimum 70%), and data collection (minimum 80%). Participants completed three patient-reported outcome measures (PROMS) detailing their psychological health, sleep quality, and intrinsic motivation to run. We extracted baseline anthropometric, biomechanical, metabolic, and training load data from their IMU/GPS wristwatch for analysis. Participants completed a weekly injury status surveillance questionnaire over the next 12-weeks. Feasibility outcomes were analysed descriptively and injured versus non-injured group differences with 95% confidence intervals were calculated for PROM/IMU/GPS data.
Results: 149 participants consented; 86 participants completed (55 men, 31 women); 21 developed an injury (0.46 injuries/1000km). Feasibility outcomes were satisfied (recruitment = 47 days; acceptance = 133/149 [89%]; adherence = 93/133 [70%]; data collection = 86/93 [92%]). Acute load by calculated effort was associated with subsequent injury (mean difference −562.14, 95% CI -1019.42, −21.53).
Conclusion: Collecting and analysing wristwatch IMU/GPS data using a commercially-available training platform was feasible in recreational runners.

1. Introduction

Recreational running offers a 40% reduction in premature mortality risk after adjusting for a comprehensive set of confounding variables (Lee et al., 2017). Recreational running can also lead to running-related injury (RRI); 50% of novice runners who cease their start to run programme by six months do so because of a RRI (Fokkema et al., 2019), whilst a cumulative incidence proportion of 46% has been reported in recreational runners over a 12-month period (Desai et al., 2021). There are a limited number of prospective studies designed to explore the aetiology of RRI (Ceyssens et al., 2019; Saragiotto et al., 2014), which limits the development of prevention strategies underpinned by robust evidence.

Most prospective cohort studies have sought to explore the association between anatomical and biomechanical variables and subsequent RRI, with the most recent data synthesis concluding that the current evidence supporting any biomechanical or anatomical variable is sparse and inconsistent (Ceyssens et al., 2019). The logistical challenges of recruiting an adequate number of participants for laboratory data collection are significant, with studies often limited by small samples (i.

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e., <100) and low numbers of events (injuries) and time points per variable (Peduzzi et al., 1996).

Whilst biomechanical and anatomical variables are often studied, focussing solely on such factors neglects the likely multifactorial nature of RRI. There is emerging evidence highlighting the need to consider additional psychological and behavioural factors in RRI development. Recent studies have reported that both inadequate sleep and poor psychological health are associated with new injury onset in a heterogeneous group of endurance athletes (Johnston et al., 2020). Recreational runners with high levels of intrinsic motivation have also been identified to sustain higher RRI rates (León-Guereño et al., 2020). These psychological factors may negatively impact training behaviours and recovery, increasing a runner's susceptibility to RRI, but to date have only been cross-sectionally associated with RRI development (Mousavi et al., 2021), prohibiting any inference of causality.

The relationship between training load and future RRI has also been recently explored, with the acute to chronic workload ratio (ACWR) proposed as a novel measurement method. ACWR is traditionally calculated by dividing acute load (distance and/or effort in the past week) by chronic load (an average of distance and/or effort from the preceding four-weeks) (Gabbett, 2016). ACWR has been explored predominantly in team sport settings, where dichotomous thresholds are associated with increased future injury risk (Blanch & Gabbett, 2016). There has been a limited exploration of the relationship between ACWR and subsequent injury in recreational runners (Maupin et al., 2020), where a higher ACWR may be protective of future injury (Nakaoka et al., 2021). There is a clear need for prospective studies with appropriate sample sizes to account for the multifactorial nature of RRI development to fully understand its aetiology.

Wearable technology platforms present a potential solution to the logistical challenges of large prospective studies and enable the collection of some biomechanical, training-load, and patient-reported data with greater ecological validity over repeated timepoints than lab-based studies. Over 75% of recreational runners use a device containing inertial measurement unit (IMU) and global positioning system (GPS) technology (Cloosterman, Fokkema, & Vos, 2022). Despite removing certain logistical barriers such as in-person laboratory testing session, prospective studies including watch- and survey-based variables still present challenges, including participant recruitment and adherence. Such wearable technology has recently been reported to be feasible for the collection of training load data (Cloosterman, Fokkema, & Vos, 2022), but to date biomechanical data or the additional collection of patient-reported sleep quality, psychological health, and intrinsic motivation data as part of a wearable technology platform has not been explored.

We aimed to investigate if collecting and analysing wristwatch IMU/GPS data using a commercially-available training platform was feasible in recreational runners. Our secondary aim was to determine if any collected baseline data were prospectively associated with subsequent RRI, to inform the development of future substantiative trials.

2. Materials and methods

2.1. Study design and ethics

We conducted a prospective longitudinal feasibility study, reported in accordance with the CONSORT pilot or feasibility extension. Ethical approval was obtained from the University of Essex ethics subcommittee one (ETH-2122-1352).

2.2. Participants

We sought a convenience sample of healthy recreational runners who met the following eligibility criteria: a) self-identify as a recreational runner; b) aged between 18 and 45; c) running for at least the past 12 months; d) have run a minimum of three times per week for at least 60 min in total in the past three-months; e) currently running pain free and have not experienced a running injury in the past six-months; f) currently partake in no more than two additional forms of exercise in addition to running each week; h) use an eligible IMU/GPS wristwatch (Garmin, Coros, Polar, Suunto, Apple). We defined an RRI as an episode of pain stopping or limiting three consecutive runs or persisting for seven days (whichever was sooner) or having sought the advice of a medical professional (Yamato et al., 2015).

2.3. Sample size

We targeted a minimum of 120 participants using an international recruitment strategy via the social media networks of the author group that covered three geographical regions (the United Kingdom, the United States of America, and Canada). Recruitment flyers were posted on X and/or Instagram by all authors, and by DashLX (Flagstaff, Arizona, USA), containing direct links to our online participant information sheet. This recruitment strategy was designed to achieve a final convenience sample of ≥100 participants following an anticipated 20% attrition, comfortably exceeding the minimum required sample for feasibility studies of 12 participants per each of the two groups (i.e., injured and healthy) (Julious, 2005).

2.4. Experimental design

We first required participants to self-declare their eligibility, report their gender (Man; Woman; Prefer not to say; I am not represented), and provide written informed consent, before completing three separate patient reported outcome measures (PROMS) using a customised Qualtrics survey (Qualtrics, Seattle, USA). Once consented, participants were asked to follow a customised link to create an account with DashLX (Flagstaff, Arizona, USA) and link their IMU/GPS wristwatch to our data repository. Participants were then asked to continue running as they desired and complete a weekly customised Qualtrics survey to determine their on-going injury status (a maximum of 12 responses per participant).

2.5. Feasibility outcomes

We defined four *a priori* feasibility outcomes for recruitment, acceptance, adherence, and data collection with reference to previously published feasibility studies with comparable methods (Cloosterman, Fokkema, & Vos, 2022; Dhokia et al., 2022). We defined successful **recruitment** as requiring a maximum of six-months to recruit 100 participants, successful **acceptance** as a minimum of 80% of eligible participants registering for a DashLX account to link their IMU/GPS device, successful **adherence** as a minimum of 70% of eligible participants completing the study, and successful **data collection** as a minimum of 80% baseline PROMS and IMU/GPS data capture.

2.6. Patient reported outcome measures

2.6.1. Mental wellbeing

We used the short Warwick-Edinburgh Mental Wellbeing Scale to evaluate mental wellbeing in the past two-weeks (Stewart-Brown et al., 2009). This PROM contains seven questions relating to future optimism, usefulness, relaxation, problem solving, clarity of thinking, closeness to others, and the ability to make up one's own mind. These were scored on a Likert scale from one (none of the time) to five (all the time) leading to a minimum score of 7 and a maximum score of 35. Individual scores were then linearly transformed using the guidance from Stewart-Brown et al., (Stewart-Brown et al., 2009) and lower scores indicated lower mental wellbeing.

2.6.2. Sleep quality

We used the brief version of the Pittsburgh Sleep Quality Index (B-

PSQI) to evaluate sleep quality in the past month (Famodu et al., 2018). This PROM contains questions in five domains: sleep latency (i.e., time taken to fall asleep), sleep duration (in hours), sleep efficiency (i.e., hours in bed relative to sleep hours), sleep disturbances (i.e., temperature, dreaming, pain, coughing/snoring), and daytime dysfunction (i.e., sleepiness and low enthusiasm). Each domain is scored from 0 to 3 points, giving a minimum total score of 0 and a maximum total score of 15, with scores of >4 indicating inadequate sleep quality (Sancho-Domingo et al., 2021).

2.6.3. Intrinsic motivation

We used the Sport Motivation Scale-6 to evaluate self-determined athlete motivation (Mallett et al., 2007). This PROM contains 24 questions in 4 categories: intrinsic motivation, identified regulation, introjected and external regulation, and amotivation. These are scored on a Likert Scale from one (does not correspond at all) to seven (corresponds exactly). These categories were combined by summing each intrinsic motivation item multiplied by +2, each identified regulation item by +1, each introjected and external regulation by −1, and each amotivation item by −2, with higher scores reflecting greater self-determined athlete motivation (Gillet et al., 2010).

2.7. Inertial measurement unit/global positioning system data

Eligible participants self-reported their height (m) and mass (kg), allowing us to calculate their BMI (kg/m^2), before linking their IMU/GPS wristwatch to their DashLX account so that their IMU/GPS data could be processed and added to our data repository. We calculated an average from all completed running sessions in the 12-weeks prior to the commencement of participants' injury surveillance for the following variables (Oeveren et al., 2021): weekly running frequency (days per week); weekly distance (km); critical power (W); cadence (steps per minute); ground contact time (ms); and stride length (m). We also calculated acute load by distance (km) and effort (unitless) as total of the 7-days prior to commencement of a participants' injury surveillance, and chronic load by distance (km) and effort (unitless) as a total of the 28-days prior to the 7-days used to calculate acute load. This allowed us to calculate ACWR (Gabbett, 2016) by dividing acute load by chronic load for both calculated distance (km) and calculated effort (unitless), which we dichotomised and defined as high when ACWR >1.5[11]. Acute/chronic load by effort is a proprietary variable calculated by DashLX designed to reflect an activity's effort-based load, calculated by dividing total power by critical power for each second run during a workout. Calculations for all IMU/GPS variables are detailed in supplementary file one.

2.8. Weekly injury survey

We sent participants a maximum of 12 consecutive weekly injury surveillance emails containing a personalised survey link (see supplementary file two). This survey was developed by evaluating the literature on common symptoms, causes, and effects of RRIs and has been used successfully in our previous work (Napier et al., 2018, 2019, 2020). This survey started with the question "In the last week, have you experienced any pain in your lower back or lower limbs" and upon selecting 'no', participants were instructed to continue running as desired as part of the study. Upon selecting 'yes', follow up questions determined the number of pain sites, pain severity (using a numerical pain rating scale), pain location using a body chart, whether the participant considered this pain running-related, level of training disruption, and whether the participant had sought the advice of a healthcare professional, to determine if they met our criteria for having developed an RRI. We automatically sent these emails every Sunday and ceased only if a participant developed an RRI. Participants that did not develop an RRI were required to respond to 75% (i.e., 9/12) emails to remain eligible. Participants that developed an RRI were required to respond every week up to their injury report to remain eligible (i.e., a participant who did not respond for 1–3 weeks and then reported an RRI the following week was considered lost to follow up for accuracy of injury reporting).

2.9. Statistical analysis

All analyses were conducted using JASP (version 0.16.2, University of Amsterdam, the Netherlands). We calculated injury incidence rate per 1000 km using raw injury counts and running exposure as part of the following formula: (# new injuries)*(1000)/(sum of all running exposure in km) (Bronner, Ojofeitimi, & Mayers, 2006). We calculated the sum of all running exposure by totalling the km run during the 12-week injury surveillance period by participants that completed the study.

We divided participants into an RRI group and a non-RRI control group and determined data normality using Shapiro-Wilk. We used normally distributed continuous data to calculate a mean difference between groups, with associated 95% confidence intervals (CIs) using the formula for Welch's *t*-test owing to unequal groups. We used non-normally distributed continuous data to calculate an average difference between groups (Hodges-Lehmann estimate) with associated 95% CIs. We used raw counts for dichotomous variables to calculate odds ratios with associated 95% CIs. P values were not presented to avoid inferring robust associations from a feasibility design, with indications of significant association inferred where 95% CI thresholds did not cross zero for continuous outcomes or one for dichotomous outcomes.

3. Results

3.1. Participants

A total of 149 eligible participants consented to participate in this study and 133 registered for a DashLX account. Ninety-three participants completed the study and 86 provided IMU/GPS data. Five different IMU/GPS devices (Garmin 80%; Coros 12%; Polar 4%; Suunto 3%; Apple 1%) were used by these participants and their baseline characteristics are detailed in Table 1. No participants identified with a gender other than man or woman and so the association of gender with subsequent RRI was analysed dichotomously.

Table 1
Baseline characteristics of eligible participants who registered for a DashLX account and those who completed the study. Data are presented as mean (standard deviation).

	ALL (N = 133)	MEN (N = 87)	WOMEN (N = 46)	ALL (N = 86)	MEN (N = 55)	WOMEN (N = 31)
VARIABLE	Eligible participants			Completing participants		
AGE (YEARS)	34.5 (7.1)	35.0 (6.7)	33.3 (7.9)	34.7 (6.9)	34.3 (6.9)	34.7 (7.0)
HEIGHT (M)	1.7 (0.1)	1.8 (0.1)	1.7 (0.1)	1.7 (0.1)	1.78 (0.1)	1.66 (0.1)
MASS (KG)	68.4 (10.3)	73.0 (8.4)	59.8 (7.7)	67.9 (9.9)	72.3 (7.6)	60.0 (8.6)
BMI (KG/M^2)	22.5 (2.3)	22.9 (2.2)	21.9 (2.4)	22.3 (2.3)	22.6 (2.0)	21.8 (2.7)
AVERAGE RUN DAYS PER WEEK	N/A	N/A	N/A	4 (2)	4 (2)	4 (1)
AVERAGE WEEKLY RUN DISTANCE (KM)	N/A	N/A	N/A	43.5 (32.3)	47.7 (36.9)	36.4 (19.4)

Notes: BMI = Body Mass Index; N/A = not applicable.

3.2. Feasibility outcomes

Recruitment commenced on October 3, 2022 and ceased on November 9, 2022; successfully completed in 47 days. We satisfied our acceptance and adherence outcomes, with 133 of 149 participants (89%) creating a DashLX account to link their IMU device and 93 of 133 participants (70%) completing the study by either responding to our minimum weekly injury survey requirement for uninjured controls (9/12; 75%) or by sustaining an RRI. We also satisfied our data collection outcome, with all 93 participants (100%) completing their PROMS, 86 of 93 participants (92%) linking their IMU/GPS device to their DashLX account, and 81 of 86 (94%) providing IMU/GPS data.

3.3. Injury incidence

Of the 86 participants who successfully completed the study and linked their IMU/GPS device, 21 (24%) met our definition of a RRI and 65 (76%) remained uninjured. A total of 45,231 km were covered by participants during the study period, equating to an incidence rate of 0.46 RRI per 1,000km. The most common injury site was the ankle (n = 5), followed by the foot (n = 4), knee (n = 4), hip (n = 4), medial tibia (n = 1), low back (n = 1), back and leg (n = 1), and global lower limb (n = 1).

3.4. Variables associated with RRI development

3.4.1. Continuous (parametric)

We identified no indication of significant association between anthropometrics, self-determined athlete motivation, weekly running volume, or chronic load by calculated effort and subsequent RRI (Table 2).

3.4.2. Continuous (non-parametric)

We identified indication of a significant association between acute load by calculated effort and subsequent RRI (Hodges-Lehmann estimate −562.14, 95% CI -1019.42, 21.53; see Fig. 1). All other analyses revealed no indication of significant association with subsequent RRI (see Table 3).

3.4.3. Dichotomous

We identified a non-significant association between the woman gender (OR 1.46, 95% CI 0.54, 4.01), inadequate sleep quality (OR 0.73, 95% CI 0.27, 1.96), high ACWR by distance (OR 2.65, 95% CI 0.73, 9.64), and high ACWR by effort (OR 1.98, 95% CI 0.51, 7.69), and subsequent RRI.

Table 2
Mean (standard deviation), mean difference between groups, and 95% confidence interval (CI) for normally distributed continuous variables.

	RRI GROUP (N = 21)	NON-RRI GROUP (N = 65)	MEAN DIFFERENCE	95% CI
HEIGHT (M)	1.7 (0.1)	1.7 (0.1)	−0.00	−0.04, 0.04
MASS (KG)	67.9 (12.5)	67.9 (9.0)	0.03	−4.92, 5.00
BMI (KG/M^2)	22.2 (2.7)	22.3 (2.1)	0.22	−0.91, 1.35
SMS-6	33.9 (18.1)	29.9 (14.9)	−4.06	−11.90, 3.76
AVERAGE RUN DAYS PER WEEK +	3.8 (2.2)	3.8 (1.7)	−0.01	−0.95, 0.93
CHRONIC LOAD BY CALCULATED EFFORT ¯	1753.7 (868.6)	1607.1 (871.3)	−146.63	−623.54, 330.29

Notes: RRI = recreational running injury; SMS-6 = sport motivation scale; +missing data from 2 participants per group; ¯ missing data from 3 participants per group.

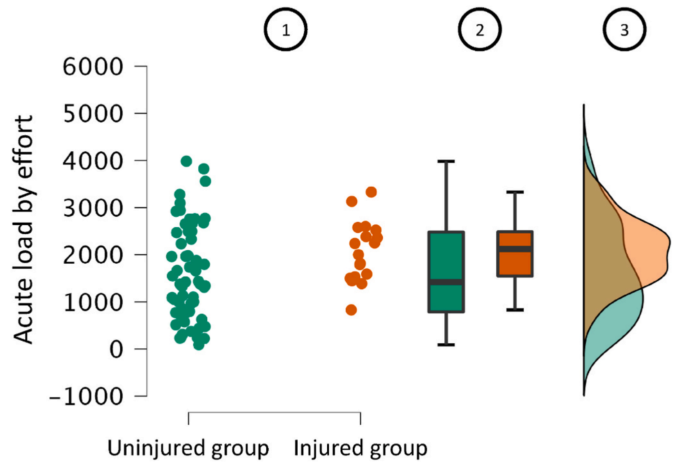

Fig. 1. Individual data points (1), box and whisker plot (2), and raincloud distribution plot (3) for acute load by calculated effort
Notes: Box plots demonstrate the median, first/third quartiles and the inter-quartile range, and minimum/maximum values in the group distribution; raincloud plot demonstrates the distribution of participants in each group relative to the y-axis.

Table 3
Median (Inter Quartile Range) and difference between groups for non-normally distributed continuous variables.

	RRI GROUP (N = 21)	NON-RRI GROUP (N = 65)	HODGES-LEHMANN ESTIMATE	95% CI
SWEMWS	24.1 (2.8)	25.0 (3.8)	0.00	−0.99,1.86
WEEKLY DISTANCE (KM) +	37.4 (39.9)	39.4 (30.4)	1.05	−14.25, 16.32
ACUTE LOAD BY CALCULATED DISTANCE =	8194.5 (5666.8)	5859.9 (5229.1)	−2120.01	−4151.21, 174.61
ACUTE LOAD BY CALCULATED EFFORT ^	2200.0 (939.9)	1421.6 (1694.4)	−562.14*	−1019.42, −21.53
CHRONIC LOAD BY CALCULATED DISTANCE #	6628.3 (6415.3)	5676.3 (4361.2)	−835.71	−3141.53, 1341.82
CRITICAL POWER (W) ¯	341.7 (106.5)	311.9 (113.1)	−22.23	−73.14, 26.98
CADENCE (SPM) ~	169.2 (10.3)	166.6 (14.9)	−1.5	−8.00, 5.40
STRIDE LENGTH (M) ~	1.0 (0.3)	1.1 (0.3)	0.00	−0.10, 0.10
GROUND CONTACT TIME (MS) ~	235.00 (11.0)	238.3 (16.6)	4.3	−3.70, 13.20

Notes: SWEMS = short Warwick Edinburgh mental wellbeing scale; spm = steps per minute; + missing data from 2 non-RRI and 1 RRI participants; = missing data from 6 non-RRI and 2 RRI participants; ^ missing data from 6 non-RRI and 3 RRI participants; # missing data from 3 non-RRI and 2 RRI participants; ¯ missing data from 3 participants per group; ~ missing data from 2 non-RRI and 4 RRI participants; * indicates possible significant association.

4. Discussion

4.1. Feasibility

We satisfied all our *a priori* feasibility outcomes. We recruited our minimum participant number in 47 days and are therefore confident that a sample of >1000 participants could be recruited for a prospective cohort at scale in a 12-month period. This may be linked to our international social media recruitment strategy and future studies using different networks or recruitment approaches may experience a different recruitment rate. Eighty-six of these recruited participants accepted an invitation to create a DashLX account to link their IMU/GPS device and 70% were adherent and completed the study. This is higher than the 63% achieved by Cloosterman et al., (Cloosterman, Fokkema, & Vos, 2022) but lower than the 84% achieved by Messier et al., (Messier et al., 2018) where a $100 gift card was offered to completing participants. Greater contact with the research team (i.e., more than once weekly via an injury survey) or an incentive is likely to be required to achieve an adherence rate of ≥80% and should be considered in future adequately powered cohorts.

All participants completing this study completed their baseline PROMS to evaluate their mental wellbeing, sleep quality, and self-determined athlete motivation. Most of these participants (86/93; 92%) linked their IMU/GPS device to their DashLX account and almost all (81/86; 94%) provided IMU/GPS data to allow for specific variables to be calculated. We are confident that a prospective longitudinal cohort study using wearable GPS/IMU technology can be run at scale and overcome the issues of small samples (i.e., <100) and low numbers of events (injuries) and time points per variable (Peduzzi et al., 1996). It is feasible to embed PROMS into IMU/GPS platforms to allow self-reported variables to be included alongside anthropometric, biomechanical, metabolic, and training load variables.

4.2. Biomechanical and metabolic variables

We identified no indication that any of our included biomechanical or metabolic variables (critical power, cadence, stride length, ground contact time) were associated with subsequent RRI. From a biomechanical perspective, cadence, stride length, and ground contact time are inter-dependent, and this may explain why none of these variables were associated with RRI in our study. Our ground contact time outcome conflicts with Weart et al., (Weart et al., 2023) who reported that active duty soldiers sustaining an RRI had a significantly longer ground contact time (mean 291ms) than those who remained uninjured (mean 277ms). The assumptions we made when calculating ground contact time as a fixed proportion of stride time may explain the conflicting findings, as compared with the measured ground contact time in Weart et al., (Weart et al., 2023). A lower cadence has also reported to be prospectively associated with tibial pain and bone stress injury in high school (Luedke et al., 2016) and collegiate (Kliethermes et al., 2021) runners, with cadence calculated using a foot-mounted IMU and three-dimensional kinematics respectively. Future prospective cohort studies designed to investigate the association of biomechanical variables and RRI should consider the limitations of wristwatch IMU data collection and consider adding distally-mounted sensors to increase data validity of some variables.

4.3. Patient reported outcome measures

We also identified no indication that psychological health, sleep quality, or intrinsic motivation were associated with subsequent RRI. Our non-significant outcome for psychological health and sleep quality conflicts with that of Johnston et al., (Johnston et al., 2020), who reported significant prospective associations with these variables and future injury in a heterogeneous group of endurance athletes. This could be explained by the difference in population (recreational runners versus heterogeneous endurance athletes) and measurement (specific patient reported outcome measures versus presence of diagnosis and sleep hours). The hazard ratios calculated by Johnston et al., (Johnston et al., 2020) were small and have upper confidence interval boundaries that are close to one. Our non-significant outcome for intrinsic motivation also conflicts with that of Leon-Guereno et al., (León-Guereño et al., 2020) though this could once again be explained by the difference in measurement tool (SMS-6 versus Behavioural Regulation in Exercise Questionnaire). As these variables have been cross-sectionally associated with injury in recreational runners (Mousavi et al., 2021), future adequately powered prospective cohorts are encouraged to continue to explore their prospective association with subsequent RRI.

4.4. Training load(s)

We identified a significant association between acute load by calculated effort (but not acute load by calculated distance) and subsequent RRI, indicating that sudden changes in running intensity may be causally associated with RRI occurrence. This did not translate to a significant association between high ACWR (>1.5) by distance or effort and subsequent RRI, though a higher percentage of runners in the injured group exceeded this threshold (effort 21%, distance 26%) compared to the uninjured group (effort and distance 12%). This conflicts with the findings of Nakaoka et al., (Nakaoka et al., 2021) who reported that a higher ACWR was inversely associated with future RRI in recreational runners (i.e., higher ACWR = lower injury risk). The conflicting result could be explained by Nakaoka et al., (Nakaoka et al., 2021) calculating ACWR only using time (weekly hours) and distance (km/week) without considering metrics of effort (intensity). Their cohort ran fewer mean days per week (2.4 versus 3.8) and fewer mean km per week (25.9 versus 38.4), indicating a probable difference in baseline conditioning. It has also been suggested that 'workload' should contain metrics of both external (distance) and internal (effort) load rather than considering these as distinct entities, and to not use arbitrary cut-off thresholds for 'high' workloads (Paquette et al., 2020). This variability in input variables for ACWR calculations and/or categorisation likely explains the conflicting data in recreational running cohorts (Paquette et al., 2020). Given there is some existing evidence for its prospective association with subsequent RRI, future cohort studies should continue to investigate all variations of ACWR. We would encourage placing particular focus on metrics of internal load (i.e., effort) combined with external load (i.e., distance/time) to reflect the non-linear relationship between magnitude and frequency of load with respect to mechanical fatigue.

4.5. Limitations and future research directions

We aimed to investigate if IMU/GPS wristwatch data collected and analysed using a commercially-available training monitoring platform was feasible for collecting prospective longitudinal data from recreational runners. Whilst we have conducted exploratory analyses between specific variables and subsequent RRI to inform future studies, we caution against making robust inferences of association from our feasibility design. It may also be that indications of non-significant association are explained by our sample size (which was determined for our feasibility outcomes) as opposed to a genuine absence of association (i.e., type II error). The fact that five different IMU/GPS devices were used by the participants in our study may also explain our indications of non-significant association, though a single brand (Garmin) was used by most participants (80%). Our adherence rate of 70% means that 40 participants were lost to follow up; data from whom may have altered our results. We calculated our injury incidence rate per 1,000km as a metric extractable from the DashLX platform. An alternative approach is to calculate injury incidence rate per 1000 h, which we were unable to export from the DashLX platform. This may have led to a different outcome, particularly if average pace varies highly throughout a cohort.

We explored running injury as a heterogeneous entity, rather than considering specific diagnoses (e.g., patellofemoral pain). It may be that significant associations exist between the variables included in our study and specific diagnoses, and future studies are encouraged to explore this hypothesis. Whilst we have identified a univariate association between acute load by calculated effort and subsequent RRI, it is unlikely that the complex entity of running injury will ever be causally explained by a single variable, especially when measured at a single timepoint. Future adequately powered cohort studies are encouraged to consider multivariate statistical approaches that analyse variables as a timeseries when exploring causal relationships. Future measures of training load should combine both external (distance/time) and internal (effort) loads with appropriate weighting to reflect the non-linear relationship between magnitude and frequency of load to optimally determine the stress experienced by recreational runners (Paquette et al., 2020).

5. Conclusions

A combined IMU/GPS data and patient reported outcome measure approach is feasible for collecting prospective longitudinal data from recreational runners and could be scaled up for an adequately powered prospective cohort study. Acute load by calculated effort was the only variable to show significant associations with subsequent RRI. Future studies should prioritise continuing to explore the relationship between training load(s) and subsequent RRI and place a particular focus on training intensity.

Ethics

Ethical approval was obtained from the University of Essex ethics subcommittee one (ETH-2122-1352).

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CRediT authorship contribution statement

Bradley S. Neal: Conceptualization, Data curation, Formal analysis, Funding acquisition, Project administration, Writing – original draft, Writing – review & editing. **Christopher Bramah:** Conceptualization, Methodology, Resources, Writing – review & editing. **Molly F. McCarthy-Ryan:** Methodology, Project administration, Writing – review & editing. **Isabel S. Moore:** Conceptualization, Methodology, Writing – review & editing. **Christopher Napier:** Conceptualization, Methodology, Resources, Writing – review & editing. **Max R. Paquette:** Conceptualization, Methodology, Resources, Writing – review & editing. **Allison H. Gruber:** Conceptualization, Methodology, Resources, Writing – review & editing.

Declaration of competing interest

Dr Bradley Neal is an editorial advisor and social media editor at Physical Therapy in Sport.

All other authors have no competing interests to declare.

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Appendix A. Supplementary data

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