The Association Between the Acute

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ORIGINAL RESEARCH ARTICLE

The Association Between the Acute:Chronic Workload Ratio and Running-Related Injuries in Dutch Runners: A Prospective Cohort Study

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Abstract

Objective To investigate the association between the acute:chronic workload ratio (ACWR) and running-related injuries (RRI).

Methods This is a secondary analysis using a database composed of data from three studies conducted with the same RRI surveillance system. Longitudinal data comprising running exposure (workload) and RRI were collected biweekly during the respective cohorts' follow-up (18–65 weeks). ACWR was calculated as the most recent (i.e., acute) external workload (last 2 weeks) divided by the average external (i.e., chronic) workload of the last 4, 6, 8, 10 and 12 weeks. Three methods were used to calculate the ACWR: uncoupled, coupled and exponentially weighted moving averages (EWMA). Bayesian logistic mixed models were used to analyse the data.

Results The sample was composed of 435 runners. Runners whose ACWR was under 0.70 had about 10% predicted probability of sustaining RRI (9.6%; 95% credible interval [CrI] 7.5–12.4), while those whose ACWR was higher than 1.38 had about 1% predicted probability of sustaining RRI (1.3%; 95% CrI 0.7–1.7). The association between the ACWR and RRI was significant, varying from a small to a moderate association (1–10%). The higher the ACWR, the lower the RRI risk.

Conclusions The ACWR showed an inversely proportional association with RRI risk that can be represented by a smooth L-shaped, second-order, polynomial decay curve. The ACWR using hours or kilometres yielded similar results. The coupled and uncoupled methods revealed similar associations with RRIs. The uncoupled method presented the best discrimination for ACWR strata. The EWMA method yielded sparse and non-significant results.

1 Introduction

Running is considered a powerful ally in physical activity promotion worldwide [1]. However, there is evidence suggesting that running-related injuries (RRI) are an important reason for novice runners to quit running practice, accounting for about half (48%) of all reasons for running discontinuation [2]. Studies have shown that 75–85% of RRIs have a gradual onset [3, 4]. Such injuries, known as overuse injuries, are characterised by a multifactorial aetiology [5, 6]. It is reasonable to assume that the workload imposed by training for sport (i.e., a combination of physiological, psychological and social strain) plays a role in the development of overuse injuries. However, there is no consensus regarding the association between training workload and sports injuries, especially the direction and/or shape of this possible association [7, 8].

The 'acute:chronic workload ratio' (ACWR) is an established measure to investigate variations of sports practice workload over time [7, 9–15]. The ACWR postulates that inappropriate workloads, such as excessive and sudden increases in training workloads (also known as spikes) related to average workload applied over the season, contribute to the development of a number of sports injuries [7, 9–16]. The ACWR provides an indicator that can be used to plan and monitor a gradual increase of the chronic workload, which might promote improvements in physical fitness and might prevent an increase in injury risk. From the ACWR perspective, this ideal training stimulus has been called the 'sweet spot' [16–18], which represents ACWRs between 0.8 and 1.3 [16].

Although the ACWR has been explored mostly in professional team sports, there is a paucity of evidence on the applicability and association between ACWR and injuries in

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Key Messages

The acute:chronic workload ratio was associated with running-related injury risk in recreational runners in an inversely proportional relationship. The higher the acute:chronic workload ratio, the lower the risk of running-related injuries.

The uncoupled and coupled methods to calculate the acute:chronic workload ratio yielded significant and similar associations with running-related injuries. The uncoupled method was the one with the best discrimination for acute:chronic workload ratio strata. The exponentially weighted moving averages method did not reach statistical significance.

Runners with an acute:chronic workload ratio under 0.70 and over 1.38 presented a predicted probability of sustaining running-related injuries of about 10% and 1%, respectively.

The acute:chronic workload ratio seems to be a reasonable marker to early identify running-related injuries in recreational runners. Therefore, runners presenting an unforeseen reduction in running workload in relation to their recent running workload history could be candidates for a health professional assessment/screening for potential running-related injuries.

Once externally validated, the acute:chronic workload ratio might be a useful tool for secondary prevention of running-related injuries.

recreational and individual sports, such as running. Therefore, the objective of this study was to investigate the association between ACWR and RRIs.

2 Methods

2.1 Study Design

This is a secondary analysis using data from three studies in recreational runners, conducted with the same RRI surveillance system in the Netherlands: (1) the *HealthyMiles* study (an 18-week prospective cohort study) [3]; (2) the *HealthyTrails* study (a 15-month prospective cohort study) [4]; and (3) the *TrailS$_6$* study (a 6-month randomised controlled trial) [19]. Each of the studies were performed in accordance with the standards of ethics outlined in the Declaration of Helsinki, and all studies were approved by the medical ethics committee of the VU University Medical Center Amsterdam.

2.2 Participants

Participants were eligible for this study if: (1) they were ≥ 18 years; (2) completed the baseline questionnaire of the respective study; and (3) reported being injury-free at baseline. The sample consisted of recreational runners. Informed consent was obtained from all participants.

2.3 Data collection

The baseline questionnaire was made available to participants via email, which included a secure link to an online form, where participants informed their age, sex, body height, body mass, running experience, history of RRIs in the last 12 months (i.e., previous RRIs) and RRIs at baseline. The respondents to the baseline questionnaire were followed-up every 2 weeks using the same email and link approach. In the follow-up questionnaires, participants informed their running exposure and any health issues experienced in the previous 2 weeks.

The Dutch version of the Oslo Sports Trauma Research Center (OSTRC) Questionnaire on Health Problems [20] was used to register experienced health issues. The OSTRC Questionnaire consists of four key questions: (1) the extent to which a health problem affected running participation; (2) running volume; (3) running performance; and, (4) the extent to which the participant experienced health symptoms during the previous 2 weeks. In case of reporting an injury, participants were invited to describe the symptoms, injury onset, if they believed that the reported injury was related to running practice and, in this case, the number of running training sessions missed (i.e., time loss) due to the reported RRI. If the health issue was not related to injury (i.e., illness), the questionnaire was terminated. Each injury report, including the injury description was captured in an open question, which was then verified by a physiotherapist (LH) to confirm or discard its relationship with running practice.

2.4 RRI Definition

RRI was defined as any symptom and/or complaint identified in any of the four OSTRC questionnaire key questions, related to the musculoskeletal (i.e., locomotor system) or integumentary (e.g., nail injuries and blisters) tissues, or concussions sustained during and/or because of running practice [3, 4, 19], that prevented the runner from participating in three or more consecutive running sessions [21].

2.5 Acute:Chronic Workload Ratio (ACWR)

The ACWR was calculated using biweekly cumulative duration of running sessions (i.e., hours of running practice) and biweekly cumulative distance of running sessions (i.e., km of running), both characterising external workload (i.e., the physical work performed by the runner) [16]. These two measures are considered valuable for the running community, since running progression is usually monitored and assessed by distance (e.g., km) and/or time (e.g., duration of run). Hours of exposure (duration) is also valuable to provide a comparable measure to other sports.

The acute running workload in the present study was derived from the most recent study follow-up period (i.e., the hours or km ran in the past 2 weeks). The chronic running workload was calculated using the average of multiple 2-week time frames preceding the most recent study follow-up period: 2, 3, 4, 5 and 6 biweekly periods (i.e., representing 4, 6, 8, 10 and 12 weeks, respectively). The ACWR was calculated by dividing the acute running workload by each chronic running workload time frame. The uncoupled [22], coupled [11], and the exponentially weighted moving averages (EWMA) [23] methods were used to calculate the ACWR.

2.6 Data Analysis

Descriptive analysis was performed to summarise the baseline data. Continuous variables were presented as mean and standard deviation (SD); discrete variables as median and 25–75% interquartile range (IQR); and dichotomous and categorical data as percentages (%) and frequency distributions (*n*). The follow-up running workload and ACWR data were summarised using linear mixed models and linear probability mixed models, to account for repeated measurements [19]. The results were expressed as mean, mean % and their 95% frequentist confidence interval (CI) [24].

Bayesian logistic mixed models were used to analyse the association between the ACWR and RRIs. The dichotomous dependent variable of these models was an indicator of reporting RRIs (1) or reporting no RRIs (0), during the respective 2-week period of study follow-up. The independent variables of interest were the ACWR and a quadratic term composed of the ACWR squared (i.e., second-order or quadratic polynomial model). The quadratic term was included in the models to allow a quadratic polynomial association in case such association being present, as postulated in previous studies on the association between ACWR and sports injuries [11, 15, 16, 23, 25–27]. Since the interpretation of polynomial models is challenging, the predicted probabilities to sustain RRIs were estimated, based on each model [28]. Thirty different models ($2 \times 3 \times 5$) were fitted to consider: (A) workload as 'duration' (in hours) and 'distance' (in km); (B) three methods to calculate the ACWR (uncoupled, coupled and EWMA); and (C) five-time frames to calculate the chronic running workload and, therefore, the ACWR (4, 6, 8, 10 and 12 weeks, respectively). The models were adjusted for age, sex, body mass index (BMI), running experience and previous RRIs. Variables indicating repeated measurements and cohorts [3, 4, 19] were included as random effects. The significance level was set at 0.05 [24].

A time-lag structure was applied to ensure that the workload data was reported before the RRI registration [29]. Therefore, the workload data of the current 2-week period was used as an independent variable for the association with RRIs reported during the next (future) 2-week period [30, 31]. All observations for each participant were considered until the end of follow-up or until the participants reported an RRI. The subsequent observations of injured participants were not considered in the analysis until they had reported to be uninjured again or until the end of follow-up. To be considered in the analysis after sustaining an RRI, the participants had to report being RRI-free for at least the same time frame of the chronic workload calculation (i.e., 2, 3, 4, 5 or 6 biweekly periods). This approach was performed to allow the models to account for subsequent RRIs.

All analyses were performed in R 3.5.0 (R Foundation for Statistical Computing, Vienna, Austria). Bayesian analyses were conducted with the 'brms' package [32]. Results were summarised, based on sampling from the posterior distributions using five chains with 20,000 interactions, and disregarding the initial 5000 interaction of each chain [19]. Summary statistics included odds ratios (OR), predicted probabilities and their 95% Bayesian highest posterior density credible interval (CrI) [24].

3 Results

A total of 435 runners, 276 men (63.4%) and 159 women (36.6%), was included in the analysis (Table 1). The median follow-up time per runner was 26 weeks (IQR 14 to 30). Average running exposure estimates during the follow-up were: frequency 2.4 (95% CI 2.1–2.7) running sessions/week; distance 25.9 (95% CI 16.8–35.1) km/week; and duration 2.9 (95% CI 2.1–3.7) hours/week. Average running workloads (i.e., acute, chronic and ACWR) during follow-up are in Table 2 and in the Electronic Supplementary Material [ESM] Tables S1–S5 and Figures S1 and S2. Detailed descriptive analyses on RRIs can be found elsewhere [3, 4, 19].

All Bayesian logistic mixed models revealed a statistically significant association between the ACWR and RRIs, except for the models using the EWMA method (Table 3 and ESM Tables S6–S10). The ORs representing the association of the ACWR in hours and RRIs were 0.21 (95%

CrI 0.13–0.32), 0.10 (95% CrI 0.03–0.27), and 0.99 (95% CrI 0.10–11.46) for the uncoupled, coupled and EWMA methods, respectively. For the ACWR in km, the ORs were 0.17 (95% CrI 0.10–0.27), 0.13 (95% CrI 0.04–0.45), and 0.54 (95% CrI 0.02–11.54) for the uncoupled, coupled and EWMA methods, respectively (Table 3).

The models using the uncoupled and coupled methods revealed that the quadratic terms were not statistically significant (Table 3), except for the models using a time frame of 6 weeks (ESM Table S7). The models using the ACWR in hours did not significantly differ from the models using the ACWR in km. Previous RRI was the only variable among those included to adjust the models that presented a consistently and statistically significant association with RRIs. The longer the time frame to calculate the chronic workload, the stronger the association between previous RRI and current RRIs (ESM Tables S6–S10).

The predicted probabilities to sustain RRIs varied from approximately 10% for the lowest ACWR quantile to approximately 1% for the highest quantile (Table 4). Figure 1 shows that the decrease in predicted probability of RRIs was steeper between the first (ACWR ≤ 0.65) and the second (0.65 < ACWR ≤ 0.90) quintiles, compared to the other 2 by 2 consecutive quintiles (i.e., second–third; third–fourth; and fourth–fifth quintiles). These results indicate that the higher the ACWR the lower the RRI risk, but in a smooth second-order polynomial decay curve (Fig. 1). The predicted probabilities for all models in this study and the respective figures describing a visual characterisation of the predicted probabilities are in the ESM Tables S11–S16 and Figures S3–S8.

Table 1 Characteristics of the runners at baseline

Variable	All participants $n = 435$	Men $n = 276$	Women $n = 159$
Age (years), mean (SD)	43.7 (9.7)	44.3 (9.6)	42.5 (9.7)
Height (cm), mean (SD)	177.2 (8.7)	181.7 (6.3)	169.3 (6.4)
Body mass (kg), mean (SD)	72.2 (10.9)	76.7 (9.2)	64.4 (8.9)
BMI (kg/m^2), mean (SD)	22.9 (2.5)	23.2 (2.3)	22.4 (2.7)
Running experience, % (*n*)			
≤ 6 months	8.0 (35)	5.8 (16)	11.9 (19)
> 6 ≤ 12 months	6.0 (26)	4.3 (12)	8.8 (14)
> 1 ≤ 2 years	14.3 (62)	14.1 (39)	14.5 (23)
> 2 ≤ 5 years	39.5 (172)	41.3 (114)	36.5 (58)
> 5 years	32.2 (140)	34.4 (95)	28.3 (45)
Previous RRI, % (*n*)	34.9 (152)	38.0 (105)	29.6 (47)

SD standard deviation, *BMI* body mass index, *RRI* running-related injury, *cm* centimetre, *kg* kilograms, *m* metre

Table 2 Descriptive analysis of the longitudinal (i.e., repeated measured over time) running workload

Variable	Hours Mean (95% CI)	Km Mean (95% CI)
Acute workload	2.9 (2.1–3.7)	25.9 (16.8–35.1)
Uncoupled approach		
Chronic workload	2.9 (2.1–3.7)	26.1 (16.9–35.4)
ACWR	1.10 (1.06–1.13)	1.09 (1.05–1.12)
ACWR categories		
≤ 0.5	15.0% (12.7–17.3)	14.4% (11.9–16.9)
> 0.5 < 0.8	17.2% (15.8–18.5)	17.2% (15.0–19.5)
≥ 0.8 ≤ 1.3	43.0% (40.5–45.5)	43.8% (41.4–46.2)
> 1.3 ≤ 1.5	10.6% (9.5–11.7)	10.1% (9.0–11.2)
> 1.5	14.4% (13.1–15.8)	14.6% (13.2–16.0)
Coupled approach		
Chronic workload	2.9 (2.1–3.7)	26.0 (16.8–35.3)
ACWR	0.99 (0.97–1.00)	0.99 (0.97–1.00)
ACWR categories		
≤ 0.5	11.6% (10.0–13.2)	11.5% (9.3–13.8)
> 0.5 < 0.8	15.9% (14.1–17.7)	16.5% (14.6–18.4)
≥ 0.8 ≤ 1.3	55.0% (52.1–58.0)	54.6% (51.7–57.4)
> 1.3 ≤ 1.5	9.1% (8.1–10.2)	9.6% (8.3–10.8)
> 1.5	8.3% (7.2–9.5)	8.1% (6.9–9.2)
EWMA approach		
Chronic workload	3.0 (2.2–3.8)	26.4 (16.7–36.2)
ACWR	1.06 (0.99–1.12)	1.06 (1.00–1.13)
ACWR categories		
≤ 0.5	0.5% (0.0–1.2)	0.4% (0.0–1.0)
> 0.5 < 0.8	6.5% (4.0–8.9)	6.6% (4.9–8.3)
≥ 0.8 ≤ 1.3	85.5% (82.9–88.0)	85.7% (83.1–88.3)
> 1.3 ≤ 1.5	3.2% (0.9–5.6)	2.6% (1.6–3.7)
> 1.5	4.0% (1.4–6.7)	5.0% (1.9–8.1)

ACWR acute:chronic workload ratio calculated using 8 weeks as a time frame, *EWMA* exponentially weighted moving averages, *CI* confidence interval

4 Discussion

4.1 Main Findings

This study investigated the association between ACWR and RRIs, using a sample composed of three cohorts applying the same RRI surveillance system [3, 4, 19]. This association was represented by a second-order polynomial decay curve, steeper between the first and second ACWR quintiles, revealing a smooth L-shaped curve. We found statistically significant associations between the ACWR and RRIs, suggesting that the higher the ACWR, the lower the RRI risk. We have below postulated three possible hypotheses that could explain our results. These explanations are not mutually exclusive, that is, they can be interpreted either

Table 3 Bayesian logistic mixed models describing the odds of sustaining RRIs when considering different ACWR approaches

	ACWR in hours			ACWR in km		
	OR (95% CrI)			OR (95% CrI)		
	Uncoupled	Coupled	EWMA	Uncoupled	Coupled	EWMA
Intercept	0.14 (0.01–1.94)	0.17 (0.01–2.41)	0.04 (0.00–0.93)	0.17 (0.01–2.40)	0.20 (0.01–3.00)	0.05 (0.00–1.10)
ACWR	0.21 (0.13–0.32)*	0.10 (0.03–0.27)*	0.99 (0.10–11.46)	0.17 (0.10–0.27)*	0.13 (0.04–0.45)*	0.54 (0.02–11.54)
Quadratic term	1.04 (0.98–1.08)	1.25 (0.67–2.16)	0.80 (0.29–1.96)	1.02 (0.89–1.10)	0.88 (0.39–1.91)	0.99 (0.24–4.10)
Age	1.01 (0.99–1.04)	1.01 (0.99–1.04)	1.01 (0.99–1.03)	1.01 (0.99–1.04)	1.01 (0.99–1.04)	1.01 (0.99–1.03)
Sex						
Man	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*
Woman	0.77 (0.49–1.20)	0.79 (0.50–1.24)	0.84 (0.54–1.31)	0.75 (0.48–1.18)	0.75 (0.47–1.19)	0.82 (0.52–1.28)
BMI	0.95 (0.87–1.05)	0.96 (0.87–1.05)	0.97 (0.88–1.07)	0.95 (0.87–1.05)	0.95 (0.86–1.05)	0.97 (0.89–1.07)
Running experience						
< 6 months	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*
> 6 ≤ 12 months	1.90 (0.58–6.62)	1.99 (0.58–6.82)	1.76 (0.52–6.47)	1.89 (0.54–6.41)	1.94 (0.55–6.71)	2.03 (0.60–7.12)
> 1 ≤ 2 years	1.89 (0.66–5.79)	2.05 (0.69–6.13)	1.52 (0.50–4.62)	1.95 (0.68–5.92)	2.11 (0.72–6.51)	1.76 (0.59–5.20)
> 2 ≤ 5 years	1.16 (0.41–3.36)	1.30 (0.46–3.76)	0.96 (0.33–2.88)	1.20 (0.43–3.44)	1.30 (0.46–3.77)	1.11 (0.40–3.26)
> 5 years	0.86 (0.30–2.58)	0.95 (0.33–2.83)	0.72 (0.23–2.14)	0.90 (0.32–2.67)	0.96 (0.33–2.88)	0.84 (0.29–2.51)
Previous RRI						
No	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*
Yes	1.64 (1.13–2.41)*	1.72 (1.16–2.52)*	1.53 (1.03–2.24)*	1.66 (1.13–2.45)*	1.71 (1.15–2.52)*	1.52 (1.04–2.24)*

ACWR acute:chronic workload ratio calculated using 8 weeks as a time frame, *EWMA* exponentially weighted moving averages, *OR* odds ratio, *CrI* Bayesian highest posterior density credible interval, *BMI* body mass index, *RRI* running-related injury

*Statistically significant

separately or combined as part of an overall explanation of our findings.

4.1.1 Explanation 1

Our results suggest a smoother and L-shape relationship between the ACWR and RRIs risk. Findings of previous studies suggested that lower and higher ACWR compared to the 'sweet spot' ACWR (i.e., coupled ACWR with a value between 0.8 and 1.3) were associated with higher sports injury risks, represented by an approximately U-shaped relationship [7, 9–11, 13]. This difference in findings can be explained by the fact that most studies so far have investigated team and professional sports, while our study has investigated an individual sport (i.e., running) and recreational athletes that may not frequently reach ACWRs beyond 1.30 (Table 2). Maybe if we had runners training/competing more often at an ACWR higher than 1.30, our analyses would have yielded higher RRI risk for higher ACWRs, approximating a U-shaped relationship. However, training/competing of an ACWR higher than 1.30 is not the recreational runner's reality, who does not vary much their weekly or biweekly ACWR (Table 2) [3, 4, 19, 33].

4.1.2 Explanation 2

The most adapted runners could be those more experienced, since training adaptation is elicited by duration of practice as well as training regimen [34–37]. Therefore, runners reaching higher ACWRs may be the most adapted ones, thus, capable of running at higher workload spikes [38–41]. Novice and even inexperienced runners usually have a lower running workload compared to more experienced runners. Therefore, they may be less adapted to running and, thus, less capable of running at higher workload spikes, resulting in lower ACWRs. Therefore, the smooth L-shaped association between the ACWR and the RRI risk found in this study could be partly explained by the trend, indicating that runners with lower RRI risk were those with higher running experience (> 5 years), and runners with higher RRI risk were those with lower running experience (≤ 2 years) (Table 3; Fig. 1b). Indeed, there is evidence suggesting that novice runners have a higher risk of RRIs [42]. These findings may suggest that changes in physical valences, as those elicited by training (e.g., lower body strength and aerobic fitness), may moderate the workload-injury relationship [37, 43].

Table 4 Predicted probabilities of sustaining RRIs when considering different ACWR approaches

ACWR quintile	Running workload in hours Predicted probability (95% CrI)	Running workload in km Predicted probability (95% CrI)
Uncoupled		
ACWR ≤ 0.65	9.6% (7.5–12.4)	10.5% (8.1–13.0)
0.65 < ACWR ≤ 0.90	5.2% (4.2–6.3)	5.0% (3.4–6.4)
0.90 < ACWR ≤ 1.10	3.6% (2.6–4.6)	3.5% (2.4–4.5)
1.10 < ACWR ≤ 1.38	2.8% (2.2–3.3)	2.3% (1.7–3.0)
ACWR > 1.38	1.3% (0.7–1.7)	1.1% (0.8–1.5)
Coupled		
ACWR ≤ 0.70	10.7% (8.2–13.4)	11.1% (8.6–13.8)
0.70 < ACWR ≤ 0.90	4.5% (3.7–5.4)	4.6% (3.4–6.1)
0.90 < ACWR ≤ 1.10	3.1% (2.2–4.0)	3.1% (2.1–4.1)
1.10 < ACWR ≤ 1.30	2.7% (2.0–4.0)	2.2% (1.5–2.8)
ACWR > 1.30	1.4% (0.9–1.9)	1.2% (0.8–1.5)
EWMA		
ACWR ≤ 0.90	4.7% (3.9–5.5)	5.1% (4.2–6.1)
0.90 < ACWR ≤ 1.00	4.7% (3.9–5.6)	4.6% (3.9–5.4)
1.00 < ACWR ≤ 1.10	4.6% (3.5–5.6)	4.4% (3.2–5.5)
1.10 < ACWR ≤ 1.20	4.7% (3.4–6.2)	4.3% (3.4–5.3)
ACWR > 1.20	4.4% (3.2–5.6)	4.1% (2.9–5.3)

Predicted probabilities presented as % means and the 95% Bayesian highest posterior density credible interval (CrI)

ACWR acute:chronic workload ratio calculated using 8 weeks as a time frame, *EWMA* exponentially weighted moving averages

4.1.3 Explanation 3

Most RRIs (about ¾) are overuse [3, 4, 19]. Therefore, the exact onset of most RRIs is difficult to identify. Injured runners at baseline were excluded from the analyses and we performed a time-lag technique [29], to ensure that the exposure data were assessed before the first RRI registration. However, it is reasonable to assume that at the time the runners reported their RRI, their running exposure over time had already been slowly influenced by the weeks of running before. If so, running exposure used to compute the ACWR could actually represent the consequence, instead of the RRI cause. This would explain why runners with lower ACWR presented a higher risk of reporting RRIs. Therefore, instead of being a causal mechanism model, we believe that the model presented in this study could be used to flag an alert to runners, coaches and/or health professionals when the ACWR reduces with no intentional reasons (differently from strategies such as tapering or periodisation) [44–46], to signal the possible development of RRIs before they are severe enough to be spontaneously recognised as such and communicated by the runners themselves. Hence, health professionals could perform screening tests or assessments to investigate the possibility of RRIs. The implication is that the model could be used as a strategy to early identify potentially injured runners who have not recognised the RRI as such yet, and then, propose an intervention programme to reduce the risk of worsening the RRI, or, preferably, to resolve the RRI.

4.2 Acute:Chronic Workload Ratio Methods

We have used three methods to calculated ACWR: uncoupled [22], coupled [11] and EWMA [47]. The uncoupled and coupled methods yielded statistically significant association between ACWR and RRIs, while the EWMA models did not reach statistical significance. The EWMA method applies more weight to more recent workloads using a time decay function [47]. This may be more sensitive in identifying workload spikes and injury risk in daily or weekly repeated measurements [7, 23, 48]. However, daily or weekly repeated measurements may be a burden for recreational athletes, and therefore, we have used biweekly repeated measurements, which might have smoothed workload variations over time. In addition, recreational runners may not periodise their training as professional and elite runners, presenting a lower variation in workload over time. With possibly lower spikes and variation in workload over time, the EWMA did not actually discriminate the recreational runners in ACWR strata as well as the uncoupled and coupled methods (Table 2), probably because weighting more recent workloads with low variations increased the

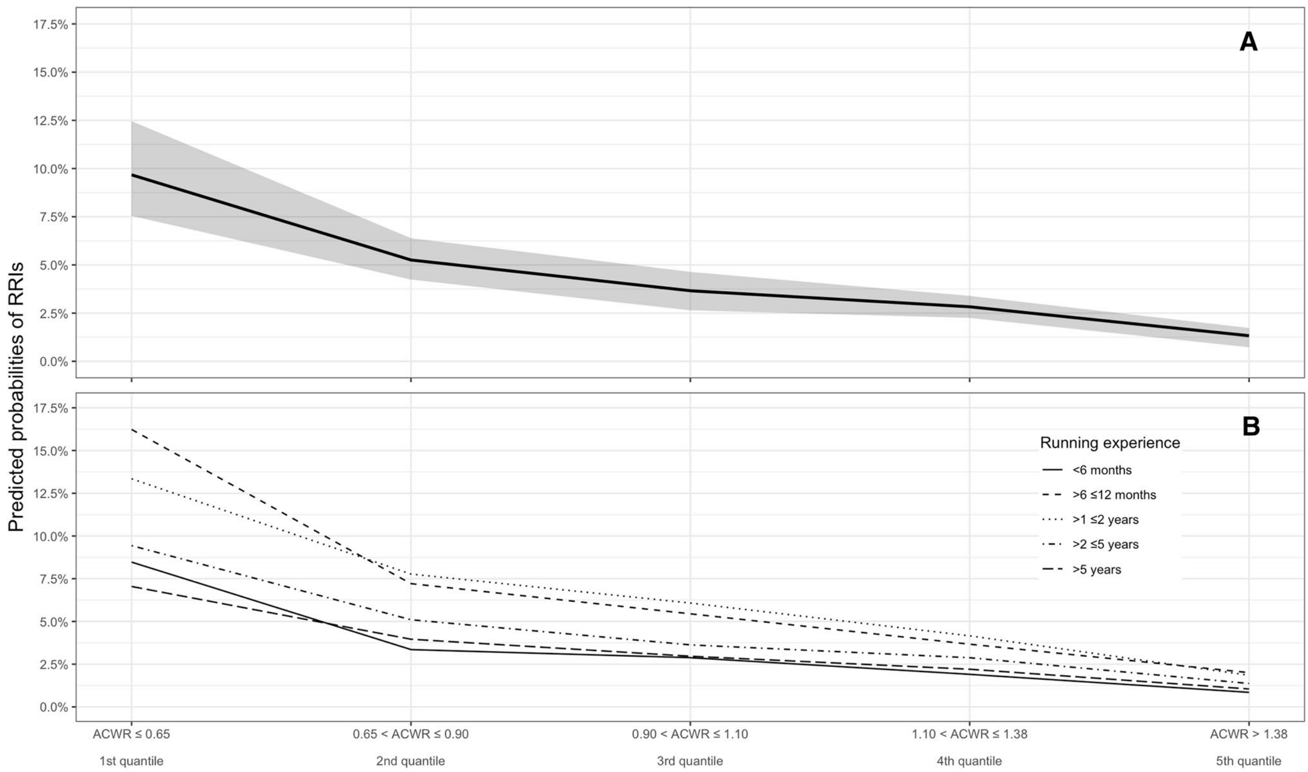

Fig. 1 Predicted probabilities of sustaining running-related injuries (RRIs). Running workload in hours was used in the uncoupled acute:chronic workload ratio (ACWR) calculation at 8 weeks. **A** Displays the predicted probabilities for all runners (the shaded area represents the uncertainty by displaying the 95% credible interval around the mean estimate). **B** Displays the predicted probabilities for runners within strata of running experience

likelihood of keeping an unchanged ACWR (i.e., ACWR closer to 1). Hence, the almost unchanged ACWR calculated with the EWMA could not go alongside RRI risk, yielding a non-significant association. The uncoupled method was the one with the best ACWR discrimination (Table 2), which was expected, since mathematical coupling mitigates the ACWR magnitude [22, 49].

With regard to the time frame used to calculate the chronic workload (i.e., 2, 3, 4, 5 and 6 biweekly periods representing weeks 4, 6, 8, 10 and 12, respectively), we found that the magnitude of the association between previous and current RRIs went higher as the time frame went longer. This finding may indicate that the association between previous and current RRIs could be mediated by chronic workload. On average, the chronic workload presented a slightly increase over time during this study (ESM Figures S1 and S2). This means that, in our sample, if we take a longer time frame, the chronic workload tends to be slightly higher. Based on this findings, further investigations on the influence of the chronic workload acting as a mediator of the association between previous and current RRI would be worthy.

4.3 Strengths

This study investigated the association between ACWR and RRIs in a large population, composed of recreational runners. Three datasets from three prospective studies (repeated measurements and the same data collection methods) were combined to increase the statistical power. This approach has advantages regarding the saving of research resources and ethics compliance, by reducing the exposure of new subjects to data collection.

The repeated measurement nature of this study has the advantage of modelling the development of time-dependent variables over time, such as running exposure (independent variable) and RRI risk (dependent variable). Even with similar summary statistics between the variables (Table 2), the way they change over time may differ significantly and may elicit new knowledge regarding the association or interaction between them. The most relevant methods to estimate ACWR were used in the data analyses: (1) to reduce the probability of spurious associations; (2) for the sake of transparency and reproducibility; and (3) to provide insights in the possibilities to investigate the association between training/competition workload and sports injuries.

The analyses performed implemented a solid and natural statistical method for population inference (i.e., Bayesian approach) [24]. Furthermore, the results were presented as predicted probabilities. We are of the opinion that presenting the results as predicted probabilities further clarifies our results and facilitates the interpretation.

4.4 Limitations

Limitations of this study should be considered when interpreting the results. To estimate sports injury risk using workload measures, both external (i.e., stress, or the amount of external work performed by the athlete, that can be measured by kilometres ran, for example) and internal workload (i.e., biomechanical, psychological and or physiological strain imposed in the athlete, that can be measured by the heart rate or the rate of perceived exertion, for example,) are important [26]. We could not aggregate data on internal workloads to the ACWR model, since the combined dataset used in this study did not contain such data.

Identifying a temporal relationship between the ACWR and RRIs may be challenging [5, 26], since most RRIs present an overuse nature [3, 4] (i.e., multifactorial origin with a gradual and not clearly identifiable onset) [5, 6]. Another limitation is that all three cohorts that provided the data were composed of convenience samples [3, 4, 19]. Ideally, although challenging, future studies should work with probabilistic or random sampling to prevent selection bias. The data in this study was collected through self-report; this can be seen as a limitation, but is considered accurate if the data collection requires short recall periods, such as in this study (i.e., every 2 weeks) [50]. In addition, all RRI reports were reviewed by a certified physiotherapist (LH) to reduce bias.

The ACWR have limitations [51–54]. These limitations include (but are not limited to): (1) the lack of a conceptual framework to support the plausibility and theoretical mechanisms explaining the influence of the ACWR on performance and/or health outcomes [52–54]; (2) some ACWR operationalisations consider the discretisation of continuous data that can be troublesome, because it is usually responsible for the loss of a considerable amount of information [52, 54], and the discretisation is very sensitive to outliers, which could result in a heavily skewed distribution [51]; (3) the increased injury risk found at lower ACWR (i.e., ACWR < 0.8) seems to lack biological plausibility [54], although a way to mitigate such limitation is the application of the time-lag structure that we adopted on our analyses in this study; and (4) the rationale for the application of the ACWR usually comes from observational studies inferring causality and/or studies with small sample sizes [52–54].

4.5 Implications

The challenge of developing temporal relationship models helping to explain the aetiology of RRIs is well recognised [55]. This ongoing challenge hinders the ability to develop primary prevention interventions focusing on RRIs. However, it is reasonable to hypothesise that we have found a data modelling approach to flag an alert to runners, coaches and/or health professionals to facilitate a possible early identification of injured runners, using the ACWR rationale. The implication for future studies is to foster further investigations on the method we have applied, to replicate and externally validate the results of our study, especially for different running populations.

The implication for clinical practice is that, once externally validated, the method proposed in this study can be implemented as a tool to help in the early identification of possible injured runners and, hence, to facilitate the provision of secondary preventive measures. These secondary preventive measures should include evidence-based advice for injured runners [19] and/or refer them to appropriate health services, to reduce the risk of worsening the RRI or, potentially, resolve the RRI.

5 Conclusions

The higher the runner's ACWR, the lower the RRI risk. The association between ACWR and RRIs was represented by a smooth L-shaped, second-order, polynomial decay curve. Risk estimates using ACWR calculated with uncoupled and coupled methods were similar, while the estimates using the EWMA calculation yielded sparse and non-significant results. Using running 'duration' (in hours) and 'distance' (in km) as running workload measures to calculate the ACWR yielded similar results.

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Declarations

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Competing interests GN, SDB, EV and LH declare that they have no conflict of interest of any nature. WvM declares for the avoidance of doubt that he is director of VU University Medical Center Amsterdam spin-out company Evalua Nederland B.V. (http://www.evalua.nl), and non-executive board member of Arbo Unie B.V. (http://www.arbounie.nl). Both companies operate on the Dutch Occupational Health Care market.

Ethics approval All studies were approved by the medical ethics committee of the VU University Medical Center Amsterdam.

Informed consent Informed consent was obtained from all individual participants included in this study.

Transparency The authors affirm that the manuscript is an honest, accurate, and transparent account of the study being reported. No important aspects of the study have been omitted. Any discrepancies from the study as planned have been explained.

Availability of data and material Data are available upon reasonable request to GN (corresponding author). De-identified participant data might be available after the consent of all authors and the privacy policy office of the VU University Medical Center Amsterdam.

Contributors LH and SDB were involved in the conceptualisation of the study. LH, EV and WvM were involved in designing and conducting the study. LH was responsible for cleaning the data and for the data analysis. All authors were involved in interpreting the data. GN drafted the first version of the manuscript. All authors revised the manuscript for intellectual content, and all approved the final version of the article. All authors had full access to the data (including statistical reports and tables) and can take responsibility for the integrity of the data and the accuracy of the data analysis.

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