applied sciences

Article

The Relationship Between Training Load and Injury in Competitive Swimming: A Two-Year Longitudinal Study

Lorna Barry [1,2,3], Mark Lyons [1,3,4], Karen McCreesh [3,5], Tony Myers [6], Cormac Powell [4,7,8] and Tom Comyns [1,3,4,*]

1 Department of Physical Education and Sport Sciences, University of Limerick, V94 T9PX Limerick, Ireland; lorna.a.barry@ul.ie (L.B.); mark.lyons@ul.ie (M.L.)
2 Performance Department, Swim Ireland, Irish Sport HQ, D15 PN0N Dublin, Ireland
3 Health Research Institute, University of Limerick, V94 T9PX Limerick, Ireland; karen.mccreesh@ul.ie
4 Sport and Human Performance Research Centre, Health Research Institute, University of Limerick, V94 T9PX Limerick, Ireland; cpowell@sportireland.ie
5 School of Allied Health, University of Limerick, V94 T9PX Limerick, Ireland
6 Sport, Exercise and Health Research Centre, Newman University Birmingham, Birmingham B32 3NT, UK; tony.myers@staff.newman.ac.uk
7 High Performance Unit, Sport Ireland, Sport Ireland Campus, D15 EPN4 Dublin, Ireland
8 Physical Activity for Health Cluster, Health Research Institute, University of Limerick, V94 T9PX Limerick, Ireland
* Correspondence: tom.comyns@ul.ie

Abstract: Training load monitoring is employed to quantify training demands, to determine individual physiological adaptions and to examine the dose–response relationship, ultimately reducing the likelihood of injury and making a meaningful impact on performance. The purpose of this study is to explore the relationship between training load and injury in competitive swimmers, using the session rate of perceived exertion (sRPE) method. Data were collected using a prospective, longitudinal study design across 104 weeks. Data were collected from 34 athletes centralised in two of Swim Ireland's National Centres. Bayesian mixed effects logistic regression models were used to analyse the relationship between sRPE-TL and medical attention injuries. The average weekly swim volume was 33.5 ± 12.9 km. The weekly total training load (AU) averaged 3838 ± 1616.1. A total of 58 medical attention injury events were recorded. The probability of an association between training load and injury ranged from 70% to 98%; however, evidence for these relationships was deemed weak or highly uncertain. The findings suggest that using a single training load metric in isolation cannot decisively inform when an injury will occur. Instead, coaches should utilise monitoring tools to ensure that the athletes are exposed to an appropriate training load to optimise physiological adaptation. Future research should strive to investigate the relationship between additional risk factors (e.g., wellbeing, lifestyle factors or previous injury history), in combination with training load and injury, in competitive swimmers.

Keywords: swimming; monitoring; training load; injury surveillance

check for updates

Citation: Barry, L.; Lyons, M.; McCreesh, K.; Myers, T.; Powell, C.; Comyns, T. The Relationship Between Training Load and Injury in Competitive Swimming: A Two-Year Longitudinal Study. *Appl. Sci.* **2024**, *14*, 10411. https://doi.org/10.3390/app142210411

Academic Editors: Herbert Schneckenburger and Arkady Voloshin

Received: 9 July 2024
Revised: 13 October 2024
Accepted: 7 November 2024
Published: 12 November 2024

1. Introduction

The connection between athlete health and performance has garnered significant research attention, particularly regarding its impact on individual and team success [1]. In individual sports, minimising training interruptions due to injury or illness is crucial for achieving performance goals [2]. Competitive swimming, with its demanding daily training volumes—often reaching 18,000 m [3]—requires meticulous planning to ensure effective training without risking under-recovery or overtraining [4,5]. Functional overreaching has been characterised by short-term performance declines from planned intensive training [5]. However, an imbalance in the training plan can lead to inadequate recovery, maladaptation and progressively non-functional overreaching or overtraining syndrome [6].

Monitoring training loads is essential for quantifying demands, informing coaches about individual physiological responses and ultimately reducing injury risks [7]. While preventing injuries involves multiple factors [8], research indicates that training load-related injuries are often preventable [9]. Common practises in competitive swimming include tracking swim volume, heart rate and the session rate of perceived exertion (sRPE) [10,11]. Despite evidence linking poor training load management to increased injury risks [12], existing studies have primarily overlooked the swimming context.

In a review, Drew and Finch [13] found moderate evidence indicating a dose–response relationship between training load and injury. However, this review only examined one study with a swimming population, leaving the results less pertinent to coaches and practitioners working in the sport. More specifically, in competitive swimming, a systematic review by Barry et al. [14] also found some evidence of a relationship between training load and injury, but no evidence of a relationship between training load and pain. Injuries included within the review had a variety of definitions including medical attention (where a qualified clinician has assessed the athlete's medical condition [15]) and/or time loss (defined as one which led to the athlete being unable to participate in full FINA activities [15]). An international survey [11] examining the training load monitoring practises in competitive swimming highlighted that 92% of responders utilised the sRPE method. However, this popular practical application is not reflected in the research being conducted in the sport. The review determined that, due to a host of methodological limitations and a clear lack of consistency in definitions and reporting, more rigorous investigations into the relationship between training load and injury in a competitive swimming population are needed. Given the methodological limitations of previous studies, there is a clear need for more rigorous, longitudinal research focusing on sRPE monitoring.

The purpose of this research is to build on these previous recommendations and explore the relationship between training load and medical attention-requiring injuries. The research objective was to utilise a prospective, longitudinal research design, which incorporates internal and external load monitoring using the sRPE method and aligns with the Federation Internationale de Natation's (FINA) (now known as World Aquatics) [15] and the International Olympic Committee's (IOC) [16] injury and illness consensus statements.

2. Materials and Methods

This study was conducted in two of Swim Ireland's National Training Centres (Limerick and Dublin) over two seasons, a 104-week period, from September 2020 to September 2022. Data collection consisted of (1) athlete self-reported data, including sRPE and session duration in minutes; (2) head coach-reported athlete attendance records and session volume (km); and (3) medical data collector (MDC)-recorded injury surveillance data. These data-reporting processes were introduced at the end of the previous season, allowing for an extensive period (12 weeks) of familiarisation with the process to occur. MDCs were provided with an injury surveillance handbook, outlining clear guidelines on the injury surveillance processes, definitions, categories and subcategories being employed. A briefing meeting was also held to discuss the data collection process.

2.1. Participants

A total of 34 athletes were recruited to take part in the study over the two-year period. All athletes at each National Centre agreed to participate, resulting in 100% recruitment of the available population. Athletes were assigned an ability level as presented in Table 1 based on the framework of McKay et al. [17]. Two athletes were removed from the final analysis. One athlete retired from swimming within eight weeks of the start of data collection due to COVID-19 training-related restrictions, while another was deemed ineligible for medical reasons. This study was approved by the University Ethics Committee (2019_10_09_EHS).

Table 1. Athlete demographics.

Variable	Male	Female
N	22	10
Age (y)	22 ± 4	18 ± 3
Height (m)	1.87 ± 0.08	1.69 ± 0.07
Body Mass (kg)	82.7 ± 6.8	61.2 ± 7.4
Tier 5—World Class	1	1
Tier 4—Elite/International	9	2
Tier 3—Highly Trained/National	12	7

2.2. Data Collection

The data collection system and procedures have been previously outlined in Barry et al. [18]. Athletes self-reported through the online Kitman Labs[TM] (https://www.kitmanlabs.com/) application, accessed through a mobile phone. Athletes rated their perceived effort for the entirety of a session on the modified Borg scale (1–10) (adapted Borg CR10 scale [19]) on the same day of completion. Athletes recorded the session duration (minutes) and activity type (i.e., swimming, S&C (Strength and Conditioning)—strength, S&C—conditioning or racing). sRPE–TL was calculated by multiplying the sRPE by the duration [20–22]. Athlete training load data were accumulated and reported as weekly training load data and included the key variables as described in Table 2. Athlete data were audited for completeness weekly.

Table 2. Description of the calculation of training load metrics.

Training Load Metric	Calculation	Description	Scaled Units
Weekly Pool Volume (km)	All session volumes (km) from Monday to Sunday are summed together to generate weekly volume.	Distance swam per week in kilometres	1.0 km
4-week Rolling Pool Volume (km)	Sum of the weekly volume for the current week and the previous three weeks.	Accumulated distance swam for 4 weeks.	10.0 km
Weekly Pool Training Load (AU)	Session RPE * Duration (minutes) = sRPE-TL. Total pool session sRPE-TL from Monday to Sunday summed together to generate weekly pool value.	Pool training load for one week.	100.0 AU
Weekly Gym Training Load (AU)	Session RPE * Duration (minutes) = sRPE-TL. Total dryland session sRPE-TL from Monday to Sunday summed together to generate weekly gym value.	Gym training load for one week.	100.0 AU
Weekly Total Load Training (AU)	Weekly pool and weekly gym values are summed together.	All training load for the week.	100.0 AU
4-week Rolling Total Training Load (AU)	Sum of the weekly total for the current week and the previous three weeks.	Accumulated training load for 4 weeks.	100.0 AU
Acute: Chronic Workload Ratio (ACWR)	$EWMA_{this\ week} = Load_{this\ week} * \lambda_a + ((1-\lambda_a) * EWMA_{last\ week})$, where λ_a is a value between 0 and 1 that represents the degree of decay, with higher values discounting older ob-servations at a faster rate. The λ_a is given by: $\lambda_a = 2/(N+1)$ where N is the chosen time decay constant, typically 7 and 28 days for acute ('fatigue') and chronic ('fitness') loads, respectively [23].	The ratio of the acute training load (past 7 days) in relation to the chronic training load (past 28 days).	0.1 AU

MDCs (chartered physiotherapists) input injury data into a bespoke Microsoft Excel worksheet, designed in line with the Orchard Sports Injury and Illness Classification System (OSIICS) [24]. MDCs were emailed fortnightly reminders to input injury information. A monthly follow-up video call to audit the data was also conducted. Injury was subcategorised as medical attention, time loss or non-time loss. Time loss was reported from the date of onset until the athlete was fully available for training or competition. 'Fully available' was clarified as without modification of training prescription, modification of technique or deficits in performance directly related to the injury. Additional information collected is described in Barry et al. [18]. Table 3 outlines the key definitions used.

Table 3. Definitions of key terms used within the injury surveillance system.

Term	Definition
Injury	Tissue damage or other derangement of normal physical function, resulting from rapid or competitive transfer of kinetic energy [16].
Medical Attention	A physical complaint where a qualified clinician assessed the athlete's physical complaint or medical condition. A qualified clinician is anyone who is involved in the health care of athletes, reviews medical or physiological information and/or implements an action plan to improve the athlete's health, where health is considered in a broad sense but must be more than performance enhancement [15].
Time Loss	A health problem which leads to the athlete being unable to take full part in FINA activities. If the athlete misses the rest of the training or competition session but returns for the next training/competition, this should be recorded as a time-loss incident [15].
Severity	Mild: 0–7 days missed; moderate: 8–28 days missed; severe: >29 days missed [15].

2.3. Statistical Analysis

Medical attention injuries (time loss/non-time loss) were recorded as a binary variable where no occurrence was noted as 0 and an occurrence was noted as 1. A lag period of 7 days was calculated for every training monitoring variable. A 7-day lag period was chosen to overcome the potential of a time loss event creating an artificial low load on the week the event occurred. A time lag was also pertinent as there has been a suggestion of a delayed effect between training load exposure and injury [9]. One week prior to injury would also represent the latest period of adjustment a coach could make to their pre-planned training week, thus making it practically relevant and impactful. All training load data were scaled as shown in Table 2. sRPE was scaled as per Tiernan et al. [25]. Descriptive analyses of athlete training loads are presented in Table 4 to investigate the occurrence of time loss and non-time loss injuries over a 7-day period, mixed-effect Bayesian logistic regression models were fitted with different predictor variables of interest. A Bayesian approach was used to circumvent the widely reported issues with the misinterpretation of traditional p-values [26] and confidence intervals (CIs) [27], to provide probabilistic interpretation of parameters and quantify uncertainty in predictions. Importantly, Bayesian models provide direct evidence for null hypotheses, given that the probability in these methods is calculated under the assumption that the null hypothesis is true.

Table 4. Descriptive summary of the key training load variables for the athletes.

Variable	Max	Min	Mean	Stdev
Weekly Pool Volume (km)	63.20	0.00	33.54	12.88
4-week Rolling Pool Volume (km)	217.00	0.00	115.99	58.64
Total Weekly Training Load (AU)	12,280.00	0.00	3838.02	1616.13
4-week Rolling Total Training Load (AU)	29,980.00	0.00	13,162.08	6535.19
ACWR (AU)	3.16	0.14	1.23	0.39

The structure of all the models was similar, with either time loss injury or non-time loss injury as the dependent variable. This dependent Y_i (below) represents a binary outcome of time loss or non-time loss injury for the ith swimmer. The likelihood for each observation is given by a Bernoulli distribution. This is a binary probability distribution of a random variable which takes a binary, Boolean output: 1 (time loss or non-time loss injury) with probability p, and 0 (no time loss or non-time loss injury) with probability $1-p$.

1. **Likelihood of Observations:**

$$Y_i \sim Bernoulli(p_i)$$

Prior knowledge for the fixed effect β and for the standard deviation σ of the random intercepts were set using Student's t-distributions with 3 degrees of freedom, a location parameter (or mean) of 0, and a scale parameter for standard deviation of 2.5 and the scale parameter for β intercepts and 3.

2. **Prior Distributions:**

$$\sigma \sim \ Student_t(3,\ 0,\ 2.5)$$

$$\beta \ \sim Student_t(3,\ 0,\ 5)$$

To determine whether these priors were appropriate, prior predictive checks were performed which generate data based on the prior predictive distribution to determine the plausibility of the prior before data are seen [28].

While dependent variables and predictor variables remained constant across model types, two different random effect structures were used for both types of injury:

(1) a series of models with each of the predictor variables of interest were fitted with a random intercept for each individual swimmer [i], which accounts for the repeated measures design of the study.

3. **Random Intercept Model:**

$$logit(p_i) = \alpha_i + \beta X_i$$

$$\alpha_i \sim N\left(0,\ \sigma^2\right)$$

(2) another series of models with the same initially fitted dependent and predictor variables were fitted with a random intercept and slope for each individual swimmer.

1. **Random Intercept and Slope Model:**

$$logit(p_i) = \alpha_i + \beta X_i$$

$$\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \sim MVN\left(\begin{bmatrix} \mu_\alpha \\ \mu_\beta \end{bmatrix}, \Sigma\right)$$

The Leave-One-Out (LOO) cross-validation method was used to determine the best models. LOO uses log-likelihoods from posterior simulations of the parameter values to estimate pointwise out-of-sample prediction accuracy. This is used to determine the relative predictive performance of each model based on existing posterior simulation draws, which are analysed using Pareto-smoothed importance sampling [29]. This method provides approximate standard errors as a by-product for estimating predictive errors and comparing predictive errors between two models. The lower the LOO information criterion (LOOIC), the better the out-of-sample prediction accuracy.

Posterior predictive checks were conducted on the best models (as determined by LOO) to assess the fit of the model to the data [30]. These checks included visual comparisons of the mean, empirical cumulative distribution function (ECDF) and density of the observed data and the posterior predictive distributions. There was no systematic discrepancy between any of the models checked and the observed data.

The posterior distributions of each of the regression coefficients for the raw coefficients and the exponentiated coefficients or ORs were calculated from the best fitting models. These coefficients were used to calculate Bayes Factors, which were calculated to quantify the evidence for the null hypothesis (that the effect of the predictor has no effect on time loss injury) versus the alternative hypothesis. The null interval was specified as −0.01 to 0.01.

Finally, the direction of the effect of predictor on time loss injury was assessed using the probability of direction. This calculates the proportion of the posterior distribution that is greater or less than zero. This provides a measure of the certainty that the effect is positive or negative.

All models were fitted using Bayesian Regression Models using the Stan (brms) package [31,32] with MCMC sampling via Stan [33]. Probability of direction and Bayes Factors were calculated using the bayestestR package [34].

A simulation study was conducted to evaluate the impact of varying sample sizes on the precision of coefficient estimates in a Bayesian mixed-effect logistic regression model to determine if the proposed sampling methodology would result in estimates that would be fit for purpose. As such, the simulation varied the number of participants and the number of observations per participant to determine precision. Precision was assessed based on the width of the credible intervals for coefficient estimates. This analysis was conducted using integrated nested Laplace approximation (INLA) [35]. While the highest precision was observed in scenarios with larger sample sizes, a configuration involving 34 participants and an average of 70 measurements per individual provides credible precision. This provides a balance between feasible data collection efforts and the achievement of statistically reliable estimates. Table 5 outlines selected results from the sampling simulation.

Table 5. Selected results from the simulation.

Number of Individuals	Observations Per Individual	Coefficient Estimate	Coefficient SE	Odds Ratio	Credible Interval Lower	Upper	Width (Precision)
20	20	0.112	0.025	1.119	1.064	1.176	0.112
34	70	0.096	0.009	1.101	1.081	1.121	0.040
40	90	0.103	0.009	1.108	1.09	1.127	0.037

3. Results

3.1. Training Load

Athletes were observed across a period of 104 weeks (two seasons). Athletes typically completed 6–10 pool sessions per week (12–20 h), depending on their specialist event. Athletes on average attended two S&C sessions per week. Across the two seasons, the average weekly volume was 33.5 ± 12.9 km. The weekly total training load averaged 3838 ± 1616, with 85% of that load coming from swimming. Figure 1 illustrates the mean weekly total training load for the athlete group as well as the weekly occurrence of medical attention-requiring injuries (time loss/non-time loss). Descriptive analyses of athlete training loads are presented in Table 4.

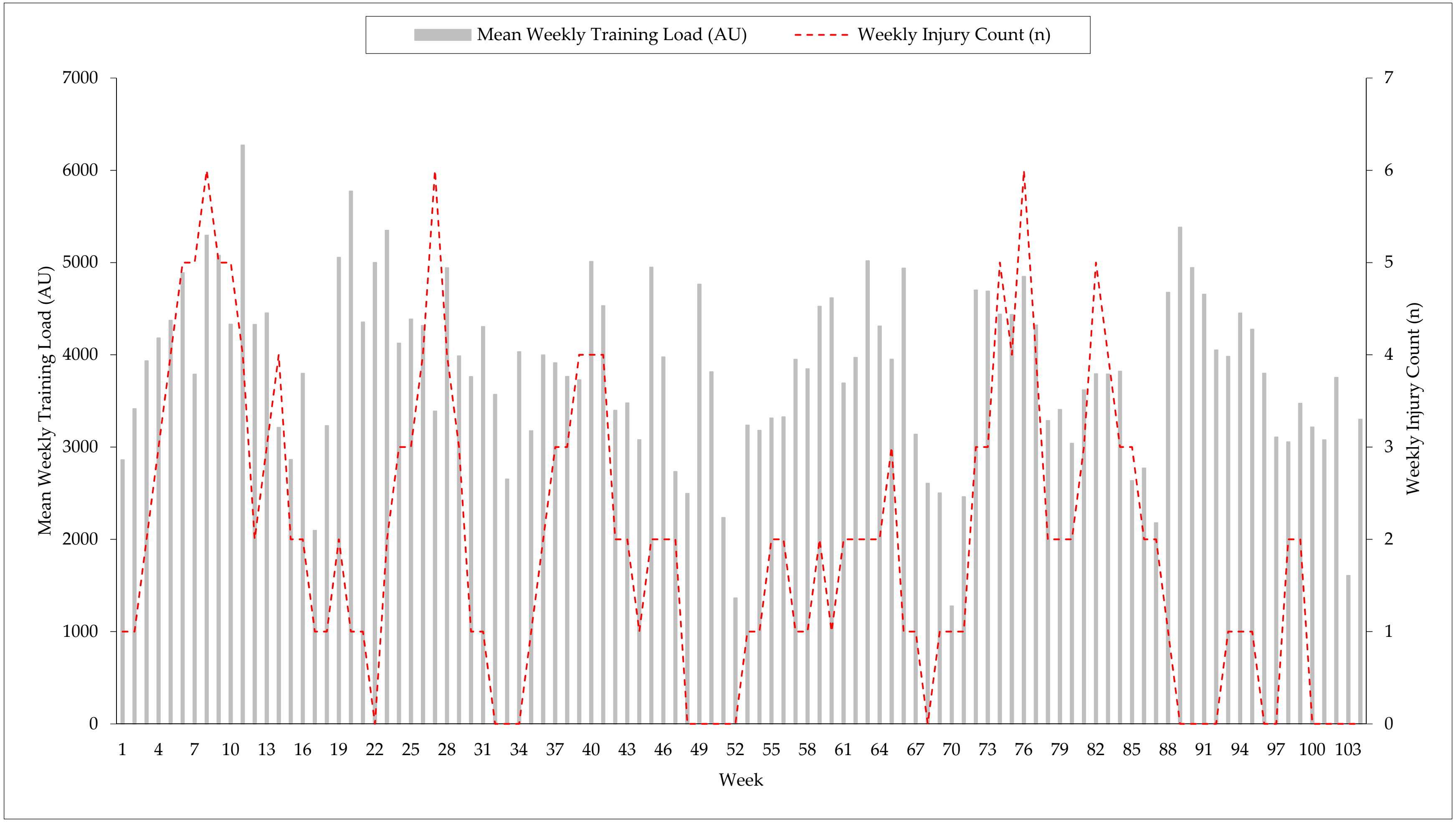

Figure 1. Mean weekly training load (AU) and weekly injury count (n) across the two-year observational period.

3.2. Injuries

A total of 58 medical attention injury events were recorded with 78.1% (n = 25) of athletes registering at least one medical attention injury event during the data collection period. Non-time loss injuries were more prevalent (63.8%, n = 37). Time loss injury severity was largely categorised as mild (95.2%, n = 20), with only one injury being categorised as moderate. "Acute—sudden onset" injuries made up 44.8% (n = 26) of all events, with "repetitive—sudden onset" (27.6%, n = 16), "repetitive—gradual onset" (25.9%, n = 15) or "mixed/other" (1.7%, n = 1) accounting for the remainder. Most injuries were sustained during either swim-specific training (46.6%, n = 27) or S&C/dryland training (34.5%, n = 20). Non-contact injuries were the most common (79.3%, n = 46) while direct contact with an object (e.g., contact with lane ropes/blocks) was also a factor (19%, n = 11)). The shoulder (24.1%, n = 14), lumbar spine (17.2%, n = 10) and ankle (12.1%, n = 7) were the locations most frequently injured.

3.3. Seven-Day Time Lag

Bayesian mixed-effect logistic regression models were employed to explore the relationship between key training load variables and the incidence of medical attention-requiring injuries (time loss/non-time loss). Table 6 outlines the results of these analyses. The probability of an association between training load and injury ranged from 70% to 98%. For most relationships explored, the log odds and Bayes Factors were close to zero. Odds ratios of one or close to one were consistent across injury types, suggesting no association between the training load variable and the odds of an injury (time loss/non-time loss) occurring. However, there was a 70% chance of positive association for ACWR with time loss injury, although the association was highly uncertain (see Figure 2). The findings for ACWR concerning non-time loss injury suggested a 97% chance of a negative relationship, although the Bayes Factor$_{10}$ suggests the data are more likely under the null hypothesis of no relationship, even though this is relatively weak evidence with high uncertainty.

Table 6. Bayesian Mixed Effects Logistic Regression, Log Odds (95% CI) and Odds Ratio (95% CI) for key training load variables and injury (time loss/non-time loss) with a 7-day lag period.

Injury Type (7-Day Lag)	Variable	Log Odds (95% CI)	Probability of the Direction Relationship	Odds Ratio (95% CI)	Bayes Factor [10]
Time loss	Weekly Pool Volume (km)	−0.02 (−0.05:0.02)	82%	0.98 (0.95:1.01)	s0
Time loss	4-week Rolling Pool Volume (km)	−0.00 (−0.01:0.00)	76%	1.00 (0.99:1.01)	0
Time loss	Weekly Total Load Training (AU)	0.00 (−0.0:0.00)	75%	1.00 (1.00:1.00)	0
Time loss	4-week Rolling Total Training Load (AU)	−0.00 (−0.00:0.01)	98%	1.00 (0.99:1.01)	0
Time loss	ACWR (AU)	0.32 (−1.54:1.60)	70%	1.51 (0.21:4.96)	0.17
Non-Time loss	Weekly Pool Volume (km)	−0.01 (−0.03:0.02)	76%	0.99 (0.97:1.02)	0
Non-Time loss	4-week Rolling Pool Volume (km)	0.01 (0.00:0.01)	76%	1.01 (1.00:1.01)	0
Non-Time loss	Weekly Total Load Training (AU)	−0.00 (−0.00:0.00)	78%	1.00 (0.99:1.00)	0
Non-Time loss	4-week Rolling Total Training Load (AU)	−0.00 (−0.00:0.00)	91%	1.00 (1.00:1.00)	0
Non-Time loss	ACWR (AU)	−0.98 (−2.19:0.04)	97%	0.38 (0.11:1.04)	0.48

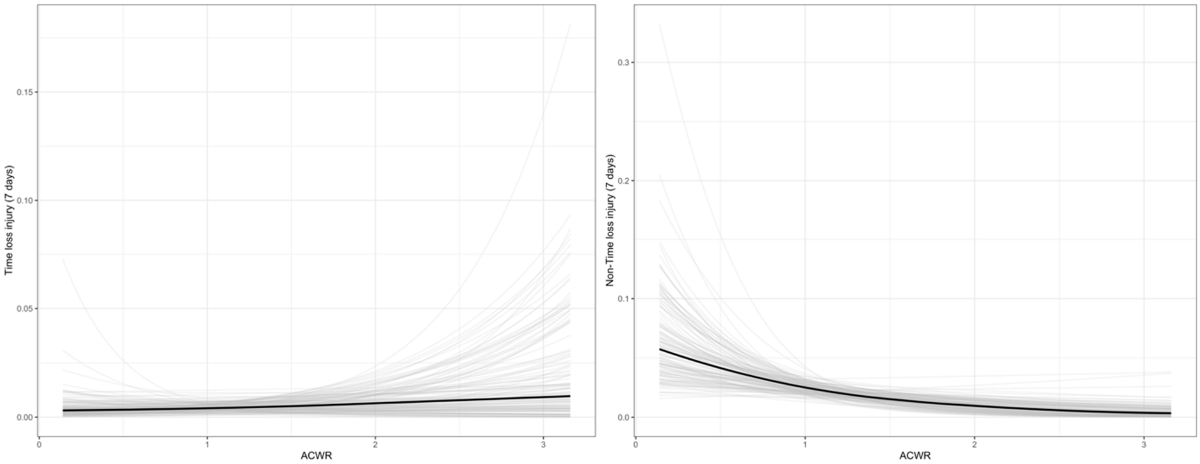

Figure 2. Spaghetti plots of the conditional effects of the relationships between injury types and Acute Chronic Workload Ratio (ACWR).

4. Discussion

This study explored the relationship between training load and injury in competitive swimmers. Fundamentally, numerous analyses examining the relationship between training load variables and medical attention-requiring injuries (time loss/non-time loss); returned ORs of 1.0 or close to 1.0 with Bayes Factor$_{10}$ suggest the data for all variables were more likely under the null hypothesis of no relationship. Therefore, these findings suggest that no relationship between the training load metric and medical attention-requiring injuries is highly likely.

Typically, Weekly Pool Volume (km), has been commonly used by swim coaches to plan and design a swim programme periodisation strategy and monitor athletes' responses to training [11]. However, using training load monitoring for injury reduction purposes has been reported as less common in an applied setting [11]. In research to date, the relationship between pool volume and injury rate has been described as "questionable" [36]. Much of the ambiguity surrounding a consensus on the relationship between these variables has been attributed to methodological inconsistencies and limitations. This study sought to address these issues.

The effect of external training load was investigated using both Weekly Pool Volume (km) and 4-week Rolling Pool Volume (km). The findings of this study suggest that neither variable had a meaningful association with injury (time loss/non-time loss). This may be related to the fact that these metrics solely consider the impact of external training load and do not incorporate internal training load nor quantify S&C training load. The investigation of the sRPE-derived metrics was a crucial aspect of the study analyses. However, the findings conclude that there is really weak evidence for any relationship with injury (time loss/non-time loss). A key finding surrounding ACWR suggested a 70% chance of positive association with time loss injury and a 97% chance of a negative relationship with non-time loss injury. However, our analyses show these findings to be highly uncertain, which, when coupled with the conclusions of Impellizzeri et al. [37] surrounding the foundations of the ACWR models, suggest that this metric should not be used as a predictor of injury.

These findings contrast with previous studies in other sports which have found a positive relationship between training load metrics and injury. Regarding elite Australian Footballers, Gabbett [38] found a reduction in absolute training load (sRPE-TL) resulted in a corresponding reduction in injuries, while Rogalski et al. [39] found that an increase in 1–2-week accumulated training load resulted in a higher risk of injury. It is very difficult, however, to compare these studies, as not only are the sports vastly different (weight bearing/non-weight bearing), but so too are the weekly training loads, and the statistical analyses make it difficult to compare findings. This issue is acknowledged by Drew and Finch [13], who noted that endurance-based sports typically display training loads with a longer duration at a lower intensity, while other sports tend to have higher-intensity training with lower durations, making comparisons difficult.

In a research context, this current study has addressed previous limitations [14,40] investigating the relationship between training load and injury. The study design presents a strong framework for future research but also for applied practitioners to understand and transfer to their environments. The findings of this study show that despite improving the methodological structure of the data collection procedures, understanding the mechanism for injury is complex and multifactorial [41]. The Bayesian approach enables direct quantification of the odds of the null hypothesis based on the data. In contrast, studies that use *p*-values cannot establish direct evidence against the null hypothesis, but only lack sufficient support for it. Rarely can the mechanism of injury be identified by exploring variables in isolation [42]. This is particularly true of an endurance sport like swimming, where the training load demands are often cited as a reason for maladaptation to occur [7]. However, while the training demands can be repetitive, they are also very systematic and are planned with care and attention in the elite setting. Figure 1 shows the training load pattern for the athlete cohort. The undulating pattern, with obvious peaks and troughs, suggests a cyclic loading pattern allowing for stress and recovery. Table 4 also highlights that the average weekly volume was 33.54 ± 12.88 km, suggesting that training volumes were planned in moderation. This may indicate that additional factors or a combination of factors could be why the training load metrics were not associated with medical attention-requiring injuries.

As suggested in Barry et al. [18], coaches typically use training load monitoring systems as a warning or communication tool. In this instance, a lack of association within this cohort could be the result of appropriate and intuitive training load management from the coaches. At this elite level, coaches frequently observe and plan their athletes' training programmes, creating an environment where minor adjustments can be made regularly. This could reduce the likelihood of injury occurring or reduce the severity of injury to a non-medical attention-requiring issue. The use of training load monitoring could be more useful in a less well-resourced training environment, where the number of athletes relative to coaches is much greater, session attendance is more variable week-to-week and individualised planning is not commonplace. However, this study reinforces that the use of this training load monitoring system is still of significant benefit to coaches by determining the athlete's physiological response to the training stimulus. Ultimately, utilising these monitoring tools to identify the competition loads and help athletes prepare for them adequately is a significant benefit. They can also be employed to compare the coaches' prescribed loads against what the athlete actually experienced and thus to create more individualised plans for athletes [43]. Finally, they can also modify any risk-adverse training load strategies that may have been implemented based on previous research conducted in other sports.

4.1. Limitations

The findings of this study are less transferable to different populations, or training programmes with vastly different training philosophies or resources available. The data collection period of the 2020/2021 season was largely carried out under a host of changing government lockdown restrictions, while the 2021/2022 season was not impacted by government-imposed COVID-19 mandates. Recent research has shown the influence of the lockdown periods on athletes [44,45]. The collection of injury surveillance data through the COVID-19 pandemic provides key information during a crucial period in elite sport; however, the validity of extrapolating the findings to less volatile periods is a potential limitation of the study.

4.2. Practical Application

The methods applied illustrate how to accurately implement such a monitoring system, but also highlight the challenge of using training load alone to prevent medical attention injuries. Coaches should acknowledge that preventing injuries is a multifactorial process and no single metric can predict an adverse event. Coaches should focus load monitoring goals on understanding the athlete's response to training and plan appropriate training progressions to meet competition demands. Training load monitoring can be particularly beneficial during high-risk training scenarios such as transitioning from a club to a collegiate programme where coaches can employ monitoring to guide their programme prescriptions using a training load passport (similar to the athlete biological passport [46]). This can ensure that the athletes are exposed to an appropriate periodised training load to optimise physiological adaptation. This training load passport would detail their training load history and inform future coaches of their training load capabilities during the transition period.

5. Conclusions

The findings suggest that no relationship between the training load metric and medical attention injury is likely. The practical applications highlight that coaches should utilise training load monitoring in combination with a global monitoring strategy to inform coaching decision-making and planning. Future research should investigate the relationship between training load and injury in a non-elite environment where training prescription may be more variable or less individualised. Similarly, future research should also expand the analysis to include medical attention-requiring illnesses, which have also been shown to affect time loss in competitive swimming [47].

Author Contributions: All authors contributed to the review conception and design. Material preparation, data collection and analysis were performed by L.B., T.C., M.L., K.M., T.M. and C.P. The first draft of the manuscript was written by L.B. and all authors commented on previous versions of the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: L.B. is funded by the Irish Research Council Employment Based Programme in conjunction with Swim Ireland (EBPPG/2019/162).

Institutional Review Board Statement: Ethical approval was granted by the University's Ethics Committee (2019_10_09_EHS), 9 October 2019.

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

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

Conflicts of Interest: Authors declare that they have no competing interests. LB is an employee of Swim Ireland, but this does not constitute a competing interest.

References

1. Drew, M.K.; Raysmith, B.P.; Charlton, P.C. Injuries impair the chance of successful performance by sportspeople: A systematic review. *Br. J. Sports Med.* **2017**, *51*, 1209–1214. [CrossRef] [PubMed]
2. Raysmith, B.P.; Drew, M.K. Performance success or failure is influenced by weeks lost to injury and illness in elite Australian track and field athletes: A 5-year prospective study. *J. Sci. Med. Sport* **2016**, *19*, 778–783. [CrossRef] [PubMed]
3. Feijen, S.; Struyf, T.; Kuppens, K.; Tate, A.; Struyf, F. Prediction of Shoulder Pain in Youth Competitive Swimmers: The Development and Internal Validation of a Prognostic Prediction Model. *Am. J. Sports Med.* **2021**, *49*, 154–161. [CrossRef] [PubMed]
4. Pollock, S.; Gaoua, N.; Johnston, M.J.; Cooke, K.; Girard, O.; Mileva, K.N. Training Regimes and Recovery Monitoring Practices of Elite British Swimmers. *J. Sports Sci. Med.* **2019**, *18*, 577–585.
5. Kellmann, M.; Bertollo, M.; Bosquet, L.; Brink, M.; Coutts, A.J.; Duffield, R.; Erlacher, D.; Halson, S.L.; Hecksteden, A.; Heidari, J.; et al. Recovery and Performance in Sport: Consensus Statement. *Int. J. Sports Physiol. Perform.* **2018**, *13*, 240–245. [CrossRef]
6. Meeusen, R.; Duclos, M.; Gleeson, M.; Rietjens, G.; Steinacker, J.; Urhausen, A. Prevention, diagnosis and treatment of the Overtraining Syndrome: ECSS Position Statement 'Task Force'. *Eur. J. Sport Sci.* **2006**, *6*, 1–14. [CrossRef]
7. Mujika, I. Quantification of Training and Competition Loads in Endurance Sports: Methods and Applications. *Int. J. Sports Physiol. Perform.* **2017**, *12* (Suppl. S2), S2–S9. [CrossRef]
8. Impellizzeri, F.M.; Menaspà, P.; Coutts, A.J.; Kalkhoven, J.; Menaspà, M.J. Training Load and Its Role in Injury Prevention, Part I: Back to the Future. *J. Athl. Train.* **2020**, *55*, 885–892. [CrossRef]

9. Gabbett, T.J. The training—injury prevention paradox: Should athletes be training smarter and harder? *Br. J. Sports Med.* **2016**, *50*, 273–280. [CrossRef]
10. Feijen, S.; Tate, A.; Kuppens, K.; Barry, L.A.; Struyf, F. Monitoring the swimmer's training load: A narrative review of monitoring strategies applied in research. *Scand. J. Med. Sci. Sports* **2020**, *30*, 2037–2043. [CrossRef]
11. Barry, L.; Lyons, M.; McCreesh, K.; Powell, C.; Comyns, T. International survey of training load monitoring practices in competitive swimming: How, what and why not? *Phys. Ther. Sport* **2022**, *53*, 51–59. [CrossRef] [PubMed]
12. Soligard, T.; Schwellnus, M.; Alonso, J.-M.; Bahr, R.; Clarsen, B.; Dijkstra, H.P.; Gabbett, T.; Gleeson, M.; Hägglund, M.; Hutchinson, M.R.; et al. How much is too much? (Part 1) International Olympic Committee consensus statement on load in sport and risk of injury. *Br. J. Sports Med.* **2016**, *50*, 1030–1041. [CrossRef] [PubMed]
13. Drew, M.K.; Finch, C.F. The relationship between training load and injury, illness and soreness: A systematic and literature review. *Sports Med. Sports Med.* **2016**, *46*, 861–883. [CrossRef]
14. Barry, L.; Lyons, M.; McCreesh, K.; Powell, C.; Comyns, T. The relationship between training load and pain, injury and illness in competitive swimming: A systematic review. *Phys. Ther. Sport* **2021**, *48*, 154–168. [CrossRef] [PubMed]
15. Mountjoy, M.; Junge, A.; Alonso, J.M.; Clarsen, B.; Pluim, B.M.; Shrier, I.; Hoogenband, C.v.D.; Marks, S.; Gerrard, D.; Heyns, P.; et al. Consensus statement on the methodology of injury and illness surveillance in FINA (aquatic sports). *Br. J. Sports Med.* **2016**, *50*, 590–596. [CrossRef]
16. Bahr, R.; Clarsen, B.; Derman, W.; Dvorak, J.; Emery, C.A.; Finch, C.F.; Hägglund, M.; Junge, A.; Kemp, S.; Khan, K.M.; et al. International Olympic Committee consensus statement: Methods for recording and reporting of epidemiological data on injury and illness in sport 2020 (including STROBE Extension for Sport Injury and Illness Surveillance (STROBE-SIIS)). *Br. J. Sports Med.* **2020**, *54*, 372–389. [CrossRef]
17. McKay, A.K.A.; Stellingwerff, T.; Smith, E.S.; Martin, D.T.; Mujika, I.; Goosey-Tolfrey, V.L.; Sheppard, J.; Burke, L.M. Defining training and performance caliber: A participant classification framework. *Int. J. Sports Physiol. Perform.* **2022**, *17*, 317–331. [CrossRef]
18. Barry, L.; Lyons, M.; McCreesh, K.; Powell, C.; Comyns, T. The design and evaluation of an integrated training load and injury/illness surveillance system in competitive swimming. *Phys. Ther. Sport* **2023**, *60*, 54–62. [CrossRef]
19. Borg, G. *Borg's Perceived Exertion and Pain Scales*; Human Kinetics: Champaign, IL, USA, 1998; p. 104.
20. Foster, C.; Florhaug, J.A.; Franklin, J.; Gottschall, L.; Hrovatin, L.A.; Parker, S.; Doleshal, P.; Dodge, C. A new approach to monitoring exercise training. *J. Strength Cond. Res.* **2001**, *15*, 109–115. [CrossRef]
21. Griffin, A.; Kenny, I.C.; Comyns, T.M.; Lyons, M. The association between the acute: Chronic workload ratio and injury and its application in team sports: A systematic review. *Sports Med.* **2020**, *50*, 561–580. [CrossRef]
22. Wallace, L.; Coutts, A.; Bell, J.; Simpson, N.; Slattery, K. Using session-RPE to monitor training load in swimmers. *Strength Cond. J.* **2008**, *30*, 72–76. [CrossRef]
23. Williams, S.; West, S.; Cross, M.J.; Stokes, K.A. Better way to determine the acute: Chronic workload ratio? *Br. J. Sports Med.* **2017**, *51*, 209–210. [CrossRef] [PubMed]
24. Orchard, J.W.; Meeuwisse, W.; Derman, W.; Hägglund, M.; Soligard, T.; Schwellnus, M.; Bahr, R. Sport medicine diagnostic coding system (SMDCS) and the Orchard sports injury and illness classification system (OSIICS): Revised 2020 consensus versions. *Br. J. Sports Med.* **2020**, *54*, 397–401. [CrossRef]
25. Tiernan, C.; Comyns, T.; Lyons, M.; Nevill, A.M.; Warrington, G. The association between training load indices and upper respiratory tract infections (URTIs) in elite soccer players. *Int. J. Sports Sci. Coach.* **2022**, *17*, 151–160. [CrossRef]
26. Wasserstein, R.L.; Lazar, N.A. The ASA statement on *p* -values: Context, process, and purpose. *Am Stat.* **2016**, *70*, 129–133. [CrossRef]
27. Morey, R.D.; Hoekstra, R.; Rouder, J.N.; Lee, M.D.; Wagenmakers, E.-J. The fallacy of placing confidence in confidence intervals. *Psychon. Bull. Rev.* **2016**, *23*, 103–123. [CrossRef]
28. Gabry, J.; Simpson, D.; Vehtari, A.; Betancourt, M.; Gelman, A. Visualization in Bayesian workflow. *J. R. Stat. Soc. Ser. A Stat. Soc.* **2019**, *182*, 389–402. [CrossRef]
29. Vehtari, A.; Simpson, D.; Gelman, A.; Yao, Y.; Gabry, J. Pareto smoothed importance sampling. *arXiv* **2015**, arXiv:1507.02646. [CrossRef]
30. Gelman, A.; Shalizi, C.R. Philosophy and the practice of Bayesian statistics. *Br. J. Math. Stat. Psychol.* **2013**, *66*, 8–38. [CrossRef]
31. Bürkner, P.-C. brms: An *R* Package for Bayesian Multilevel Models Using Stan. *J. Stat. Softw.* **2017**, *80*, 1–28. [CrossRef]
32. Bürkner, P.-C. Advanced Bayesian Multilevel Modeling with the R Package brms. *R J.* **2018**, *10*, 395. [CrossRef]
33. Stan Development Team. RStan: The R Interface to Stan. 2023. Available online: https://mc-stan.org/ (accessed on 17 January 2024).
34. Makowski, D.; Ben-Shachar, M.; Lüdecke, D. bayestestR: Describing Effects and their Uncertainty, Existence and Significance within the Bayesian Framework. *J. Open Source Softw.* **2019**, *4*, 1541. [CrossRef]
35. Rue, H.; Martino, S.; Chopin, N. Approximate Bayesian inference for latent Gaussian models by using integrated nested laplace approximations. *J. R. Stat. Soc. Ser. B Stat Methodol.* **2009**, *71*, 319–392. [CrossRef]
36. Lippincott, E.L. *Predictors of Shoulder Injuries in Female Collegiate Swimmers*; Nova Southeastern University: Fort Lauderdale, FL, USA, 2018; Available online: https://nsuworks.nova.edu/cgi/viewcontent.cgi?article=1070&context=hpd_pt_stuetd (accessed on 18 February 2023).

37. Impellizzeri, F.M.; Woodcock, S.; Coutts, A.J.; Fanchini, M.; McCall, A.; Vigotsky, A.D. What role do chronic workloads play in the acute to chronic workload ratio? Time to dismiss ACWR and its underlying theory. *Sports Med.* **2021**, *51*, 581–592. [CrossRef]
38. Gabbett, T.J. Reductions in pre-season training loads reduce training injury rates in rugby league players. *Br. J. Sports Med.* **2004**, *38*, 743–749. [CrossRef]
39. Rogalski, B.; Dawson, B.; Heasman, J.; Gabbett, T.J. Training and game loads and injury risk in elite Australian footballers. *J. Sci. Med. Sport* **2013**, *16*, 499–503. [CrossRef] [PubMed]
40. Trinidad, A.; González-Garcia, H.; López-Valenciano, A. An updated review of the epidemiology of swimming injuries. *J. Inj. Funct. Rehabil.* **2021**, *13*, 1005–1020. [CrossRef]
41. Clifton, D.R.; Grooms, D.R.; Hertel, J.; Onate, J.A. Predicting injury: Challenges in prospective injury risk factor identification. *J. Athl. Train.* **2016**, *51*, 658–661. [CrossRef]
42. Edouard, P.; Ford, K.R. Great challenges toward sports injury prevention and rehabilitation. *Front. Sports Act. Living* **2020**, *2*, 80. [CrossRef]
43. West, S.W.; Clubb, J.; Torres-Ronda, L.; Howells, D.; Leng, E.; Vescovi, J.D.; Carmody, S.; Posthumus, M.; Dalen-Lorentsen, T.; Windt, J. More than a metric: How training load is used in elite sport for athlete management. *Int. J. Sports Med.* **2020**, *42*, 300–306. [CrossRef]
44. Tondelli, E.; Zabaloy, S.; Comyns, T.M.; Kenny, I.C. Effect of COVID-19 lockdown on injury incidence and burden in amateur rugby union. *Phys. Ther. Sport* **2023**, *59*, 85–91. [CrossRef] [PubMed]
45. Waldén, M.; Ekstrand, J.; Hägglund, M.; McCall, A.; Davison, M.; Hallén, A.; Bengtsson, H. Influence of the Covid-19 lockdown and restart on the injury incidence and injury burden in men's professional football leagues in 2020: The UEFA elite club injury study. *Sports Med.-Open.* **2022**, *8*, 67. [CrossRef] [PubMed]
46. Athlete Biological Passport. World Anti-Doping Agency. Available online: https://www.wada-ama.org/en/athlete-biological-passport (accessed on 15 February 2024).
47. Prien, A.; Mountjoy, M.; Miller, J.; Boyd, K.; Hoogenband, C.v.D.; Gerrard, D.; Cherif, M.Y.; Lu, Y.; Nanousis, K.; Liscano, E.I.O.; et al. Injury and illness in aquatic sport: How high is the risk? A comparison of results from three FINA World Championships. *Br. J. Sports Med.* **2017**, *51*, 277–282. [CrossRef] [PubMed]