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The evaluation of acute: Chronic workload ratios for integration into the injury mitigation strategy of a sport organization.

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THE EVALUATION OF ACUTE:CHRONIC WORKLOAD RATIOS FOR INTEGRATION INTO THE INJURY MITIGATION STRATEGY OF A SPORT ORGANIZATION

By

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ABSTRACT

THE EVALUATION OF ACUTE:CHRONIC WORKLOAD RATIOS FOR INTEGRATION INTO THE INJURY MITIGATION STRATEGY OF A SPORT ORGANIZATION

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The use of the acute:chronic workload ratio (ACWR) is a strategy presented as a means of mitigating the injury risk athletes are exposed to from their regular participation in sport. However, the current literature is inconclusive towards its effectiveness at actually mitigating injuries. The purpose of this dissertation was to determine if ACWR should be integrated into an injury mitigation strategy of a sport organization and, if so, what input, computation, and injury-related methodologies should be used with it.

Retrospective injury data and velocity-based distances from training and competition demands from collegiate women's field hockey athletes were used to investigate the significance of ACWR methodologies within the context of ACWR computation, injury likelihood profiling, and injury mitigation strategy (IMS) performance. Factors included injury definition and lag period, input, averaging and coupling method, and acute and chronic time frame. Levels within each factor were based on methods from the literature. A case study was also presented investigating the accuracy, sensitivity, and specificity of all configurations using a threshold optimized for peak accuracy. A selected configuration was then used to evaluate the performance of an

IMS using varied thresholds, the injury likelihood profile, and flagged injuries relative to a seasonal timeline and injury type.

Within each application, the effects of a given factor should not be interpreted without considering its interactions with other factors and factor levels. The impact of each factor fell within a hierarchical order where considerations for injury criterion factors were more important than input and considerations for input were more important than factors within the ACWR computation model. The injury likelihood profile, performance curves, and flagged injuries should be used to evaluate the development of the ACWR criteria.

This dissertation concluded the use of ACWR provides information that supports injury mitigation decisions and efforts. However, the utility of ACWR depends on how it is applied, and there is not a universal configuration for its implementation. Further research should be directed at backtesting and optimizing injury mitigation strategies to maximize their practical impact.

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CHAPTER 1

INTRODUCTION

A prominent problem of a sport organization promoting the health and well-being of its athletes is mitigating the injury risk athletes are exposed to from their regular participation in sport. A potential solution for that problem is to progressively develop an injury mitigation strategy and utilizing the acute:chronic workload ratio (ACWR) may be a tactic to support that strategy. Sport practitioners can use the ratio to quantify the physical demand of sport-related activities, link that demand to injuries, and then re-structure or progress sport development so athletes become more resilient to those injuries. Because sport-related injuries are a multifactorial problem, ACWR can be integrated into a multifactorial solution. However, the current research encompassing ACWR is inconclusive towards how effective it is at mitigating injuries. The purpose of this dissertation was to determine if ACWR should be integrated into an injury mitigation strategy and, if so, what input, computation, and injury-related methodologies should be used with it.

When evaluating whether ACWR should be part of an injury mitigation strategy, knowledge is needed with respect to how injuries occur, how to link sport demand to injuries, and how to quantify sport demands. This chapter describes factors influencing sport injury aetiology, discusses the quantification of volume and intensity in sport using global positioning systems (GPS) and reviews the utility and computation of ACWR's. This chapter also summarizes how the following chapters will investigate if ACWR's should be used to mitigate injuries from sport participation.

Sport Injury Aetiology

Kalkhoven et al. proposed a generalized framework for athletic injury aetiology that emphasized the interplay between tissue loading and tolerance and considered the impact of various factors on tissue resilience and failure (Kalkhoven, Watsford, and Impellizzeri 2020). Bones, ligaments, tendons, and skeletal muscles were the bodily tissues included within the framework, and the primary factors leading to injuries consisted of individual physiology, tissue mechanical properties, and applied external forces.

Physiology determines the mechanical properties of tissues and the physical performance attributes of an athlete, which contribute to the forces an athlete is exposed to and the capacity of their tissues to tolerate the load. Factors influencing the physiology of an individual include modifiable and non-modifiable intrinsic factors and extrinsic factors. Intrinsic factors occur within an individual while extrinsic factors are external, and modifiable factors can be changed while non-modifiable cannot. Modifiable, intrinsic factors include muscle structure, tendon structure, bone mineral content, body composition, and others. Non-modifiable, intrinsic factors include age, genetics, anatomy, menstruation, and others. Extrinsic factors include workload, training method, nutrition, medication, and others. Though many factors contribute to injuries, workload will be the primary focus for developing the relationship between acute:chronic workload ratios and injuries.

Mechanical properties, such as ultimate strength and stiffness, govern how a tissue responds to an applied load, and some tissues can acutely adapt to the loads they are exposed to while others require chronic adaptation. Strength of a tissue refers to its capacity to withstand an applied load, while stiffness describes the relationship between an applied force and the deformation of a tissue. Stiffness also represents the ratio of stress to strain within the elastic region of deformation (Hooke's Law); though specific tissues can have different behaviors than others (Baumgart 2000; Rodgers and Cavanagh 1984). When an athlete engages in a sport-related activity, the workload they accumulate induces stresses and strains on their tissues, and the impact of those stresses and strains are accommodated by tissue strength and stiffness.

Tissues can undergo loading from external forces that vary in magnitude, direction, and frequency, and the interaction between external forces and strength contribute to the load tolerance of a tissue. The loading pattern of a given force can vary from discrete to continuous to cyclical with high to low magnitudes, and the resulting damage becomes dependent on the loading pattern and number of cycles. The external forces experienced by an athlete are specific to the demands of training and competition, and those demands can be generally represented by the volume, intensity, and frequency of workloads.

The combination of individual physiology, tissue mechanical properties, and applied external force induce stresses and strains on the respective tissue that can lead to microdamage and macrodamage. Microdamage occurs when a tissue experiences mechanical fatigue in response to cyclic or repetitive loading, and it is characterized by the accumulation of tissue damage and the progressive diminishment of stiffness and strength (Edwards 2018). The resulting physiological response to microdamage changes the mechanical properties of the tissue through acute and chronic adaptations that make the tissue more resilient to future exposures of similar loads. If further microdamage occurs before an adaptation can make a tissue more resilient, an overuse or chronic injury occurs. Macrodamage results in an acute injury when there is a failure in the structure of a tissue. Failure occurs when the strength of a structure or material is exceeded by excessive stress and strain caused by either the application of a singular high-magnitude stress or alternatively repeated applications of load at some percentage of a material's ultimate strength (Peterson 1950). Though tissue loading and tolerance may be the direct mechanisms of an injury, indirect factors that impair the function of a tissue could also contribute to an injury.

GPS Application to Sport

Training and competition workloads contribute to tissue loading, and the adverse interactions of that loading with an individual's physiology and tissue material properties can lead to injuries. In outdoor team sports, training and competition workloads can be quantified using a global navigation satellite system (GNSS), such as a global positioning system (GPS). A GPS satellite transmits a radio signal containing its position and the time the signal was sent, and a GPS receiver receives the signal at some final time. The receiver determines the time it took for the signal to travel from the satellite to the receiver and then calculates the distance from the satellite to the receiver by multiplying the travel time by the speed of the signal (speed of light). When the distances of the receiver from at least three satellites are known, the receiver can determine its latitudinal and longitudinal position using trilateration. After the receiver identifies two positions, the distance the receiver has traveled is determined by the fundamental equations and error corrections of a company's proprietary processes. Techniques have been developed to improve the accuracy of GPS data with some systems providing positioning within inches or centimeters of the actual object, and movement demands measured with 10 Hz GPS devices have been shown to have greater validity and inter-unit reliability than 1, 5, and 15 Hz devices (Johnston et al. 2014).

The GNSS within Optimeye (Catapult Sports, X4) and Vector (Catapult Sports, S7) devices and their proprietary data processing has been externally accessed to provide valid measures of position, distance, and velocity as well as inter-unit reliability. Linear and multi-directional movements were performed in a small space and determined to be comparable to metrics from a Vicon motion capture system. Within training environments, maximum velocities were comparable to those measured by a Stalker ATS II radar system while total distances were comparable to measured distances from a tape measure. Distance and position were also accessed at varying locations inside a stadium that could be affected by the structure of the stadium. Furthermore, Optimeye and Vector devices receive satellite signals at 10 Hz, and the velocity-based metrics are processed at the 10 Hz level.

Velocity-based distances of a session represent the accumulation of the respective distance within active periods and rotations, established by the sport practitioner live or retroactively, across an activity. Total distance is the accumulated distance from a session. A velocity-based distance is the distance accumulated above or below a velocity or within a velocity band. The velocity bands used by the University of Louisville Athletics Sport Science department for female athletes are: less than 0.10 m/s for velocity band 1, 0.10 to less than 1.70 m/s for velocity band 2, 1.70 to less than 3.00 m/s for velocity band 3, 3.00 to less than 4.00 m/s for velocity band 4, 4.00 to less than 5.00 m/s for velocity band 5, 5.00 to less than 6.00 m/s for velocity band 6, 6.00 to less than 7.00 m/s for velocity band 7, 7.00 m/s and greater for velocity band 8. The velocity bands can be sequentially added together to create 36 different velocity-based distances. The literature currently investigates the use of velocity-based distances as inputs to ACWR, such as low, moderate, and high intensity running distances; low speed, moderate speed, high speed, and very high speed distances; and various other distances.

Acute:Chronic Workload Ratios and Model Configuration

The acute:chronic workload ratio (ACWR) is an index of an athlete's current workload from training and competition relative to what the athlete is prepared for (Gabbett 2016) and has been used to associate workloads athletes are exposed to from sport participation to the injuries resulting from that participation (Soligard et al. 2016). ACWR was originally introduced as training-stress balance and was calculated by dividing acute workload (AW) by chronic workload (CW), where AW and CW were the averages of total balls bowled in cricket over the previous week and four weeks, respectively (Hulin et al. 2013). However, the literature has since shown many inputs and configurations being used to determine ACWR with cautioned recommendations regarding which methodologies are effective for mitigating injuries from sport participation (Andrade et al. 2020; Griffin et al. 2020). When considering ACWR as part of an injury mitigation strategy, averaging method, coupling method, and time frames for the acute and chronic workloads should be evaluated with respect to a given input.

The moving average method is separately applied to the numerator and denominator of the ACWR and has been implemented as a rolling average (RA) or exponentially weighted moving average (EWMA) on a daily or weekly basis (Andrade et al. 2020; Griffin et al. 2020). RA's apply equal weights to each load while EWMA's apply non-linear decreasing weights to each load as the time from which that load occurred increases from a given day (Williams et al. 2016). RA ACWR is determined by dividing the average workload of the acute time frame by the average workload of the chronic time frame. EWMA has been suggested to be a better model than RA because it accounts for the decaying nature of fitness and fatigue effects over time and the non-linearity of injury occurrence and workload (Williams et al. 2016), where acute responses and chronic adaptations in bodily tissues affect cellular disturbances during subsequent training sessions (Hawley 2002). EWMA ACWR is determined by dividing the acute workload EWMA by the chronic workload EWMA. EWMA for the respective workload is calculated using

$$EWMA_{today} = Load_{today} \times \lambda_a + \left((1 - \lambda_a) \times EWMA_{yesterday}\right) \tag{1}$$

where λ_a is the degree of decay. The degree of decay is calculated using

$$\lambda_a = 2/(N + 1) \tag{2}$$

where N is the time decay constant, which is the acute or chronic time frame for the respective EWMA.

Coupling method affects the loads used within the chronic workload. When ACWR is coupled, the loads used within the acute workload are also included in the chronic workload. When a coupled ACWR numerator and denominator have the same loads, the ratio of total acute and chronic loads will not exceed one. As a result, the theoretical limit of a coupled ACWR will be determined by the ratio of the chronic and acute time frame. When using 1-week acute and 4-week chronic time frames, ACWR will not exceed four (Windt and Gabbett 2019). This can practically occur at the onset of training or following an extended period of no training. Furthermore, a coupled ACWR may be subjected to biased inferences from a spurious correlation (Lolli et al. 2019), where a correlation exists between two variables irrespective of any true physiological association between those variables (Pearson 1897; Tu and Gilthorpe 2007). When ACWR is not coupled, the chronic workload excludes the loads used within the acute workload allowing for the ratio of total acute and chronic loads to exceed one, and ACWR is only limited by the data used within the calculation.

Physiologically, acute responses to training are the cellular alterations that occur following a single session and chronic adaptations are the modifications in cells that persist for extended periods of time (Booth and Thomason 1991). Consequently, acute time frames of 3-14 days and chronic time frames of 2-8 weeks have been used within ACWR computations to quantify the physical demand associated with acute and chronic responses to training (Griffin et al. 2020; Andrade et al. 2020). It has also been suggested that acute and chronic time frame selection may be specific to the periodized demands or training structures of a sport (Griffin et al. 2020; Andrade et al. 2020; Carey et al. 2017).

Chapter 2 Overview

Many ACWR inputs and computational configurations have been investigated in the literature, but it is unclear which combination(s) should be used to effectively mitigate injuries. Though studies have investigated the main effects of some computation factors, the methodologies of those studies held all other factors except one constant and did not include interaction effects. Consequently, Chapter 2 was used to vet ACWR methodologies in the literature, and the results were compared to corresponding effects on injury likelihood and peak accuracy of an injury mitigation strategy in Chapters 3 and 4, respectively.

Acute:chronic workload ratios require an input and computation configuration. The inputs used to determine ACWR consisted of velocity-based distances from GNSS signal receiving devices. The computation configuration included an averaging method, coupling method, acute time frame, and chronic time frame. The averaging method contained rolling average and exponentially weight moving average factor levels, while the coupling method contained coupled and not coupled factor levels. The acute and chronic time frames ranged from 3-14 days and 2-8 weeks, respectively.

The purpose of Chapter 2 was to determine the main and interaction effects of input and computation factors and factor levels on ACWR. Factors with significant effects were further investigated to determine which factor levels within the respective factor had differing effects and how the differing effects affected ACWR.

Chapter 3 Overview

Injury likelihood is commonly associated with ACWR within the literature and used to make decisions regarding the management of training and competition workloads in sport environments. In order to provide support for the use of ACWR in a practical injury mitigation strategy, the ACWR and additional injury likelihood methodologies need to be evaluated together.

An injury likelihood profile introduces effects from injury definitions, injury lag periods, binning processes, and curve fitting functions in addition to ACWR inputs and computation configurations. A general and specific injury definition was included in Chapter 3 as well as a range of injury lag periods from no lag to 28 days. A binning optimization approach was used, which is not currently featured in the injury likelihood literature, and a spline function was created for each profile using a standard procedure. Acute:chronic workload ratios and the corresponding inputs, averaging methods, coupling methods, acute time frames, and chronic time frames from Chapter 2 were included in this chapter.

The purpose of Chapter 3 was to determine the effects of input and computation factors and factor levels on injury likelihood. Factors with significant effects were further investigated to determine which factor levels within the respective factor had differing effects and how the differing effects affected injury likelihood. The factors and factor levels that affect ACWR in Chapter 2 may no longer be significant to injury likelihood due to the additional methodologies for determining it.

Chapter 4 Overview

Accuracy is a tool used in clinical research to assess how well a given intervention correctly identifies a true event. When developing an injury mitigation strategy, performance parameters such as accuracy may be more practical than injury likelihood because it is based on actual outcomes rather than the probability of an outcome caused by sport participation. Though some ACWR studies have briefly mentioned performance parameters such as sensitivity and specificity, no studies were identified that have investigated the effects of methodological decisions on accuracy. Methodologies that have a significant increasing effect on accuracy would be preferred over others.

Similar to injury likelihood, the accuracy of an injury mitigation strategy is based on configurations consisting of ACWR input, averaging method, coupling method, and acute and chronic time frames in addition to injury definition and injury lag periods. Chapter 4 presents an approach to evaluating methodological configurations by varying an ACWR threshold to maximize the accuracy of each configuration relative to an injury criterion.

The purpose of Chapter 4 was to determine the effects of input and computation factors and factor levels on the accuracy of an injury mitigation strategy. Factors with significant effects were further investigated to determine which factor levels within the respective factor had differing effects and whether differing effects increased, decreased, or had no effect on accuracy. The factors and factor levels that affect ACWR in Chapter 2 may no longer be significant to accuracy due to the additional methodologies for determining it. Furthermore, the factors and factor levels that affect injury likelihood in

Chapter 3 may have different effects than those on accuracy even though the same methodological factors are used.

Chapter 5 Overview

Due to the vast matrix of ACWR configurations possible from the literature, there may still be several potential configurations for an IMS after factor levels that are not statistically different are reduced. Those configurations could be further evaluated by backtesting strategies and optimizing the variable parameters within the strategies. Though backtesting is beyond the scope of this dissertation, this chapter explores opportunities for integrating backtesting and optimization into the development of injury mitigation strategies.

The purpose of Chapter 5 was to present a retrospective case study that investigated various aspects of an ACWR-based injury mitigation strategy. Those aspects include the sensitivity and specificity of all methodological configurations optimized for peak accuracy in addition to the injury likelihood profile and accuracy, sensitivity, and specificity of a strategy relative to an ACWR threshold for a selected configuration. The flagged and missed injury instances relative to the timeline of the competitive season and the types of injuries that occur are also discussed.

CHAPTER 2

EFFECTS OF VELOCITY-BASED INPUTS AND COMPUTATION METHODS ON ACUTE:CHRONIC WORKLOAD RATIOS IN WOMEN'S COLLEGIATE FIELD HOCKEY

Background and Significance

The acute:chronic workload ratio (ACWR) is a tool presented within the literature as a means of quantifying an athlete's current workload from training and competition relative to what the athlete is prepared for (Gabbett 2016) and has been used to associate the workloads athletes are exposed to from sport participation to the injuries resulting from that participation (Soligard et al. 2016). However, the literature has shown many model inputs and computational configurations being used to determine ACWR with cautioned recommendations regarding which methodologies yield ACWR values that better inform the development of injury mitigating strategies (Andrade et al. 2020; Griffin et al. 2020).

Global positioning system (GPS) based measures are the most common external training metrics that have been used as ACWR inputs (Andrade et al. 2020). Those metrics have consisted of total distance; low-, moderate-, and high-intensity running; low-, moderate-, high-, and very high-speed distances; sprint distance; and others with many of the same metrics using inconsistent velocity bands or thresholds between studies. The literature currently shows ACWR is associated with injury risk when used with measures of external training load (Griffin et al. 2020); however, it does not conclusively support or reject the use of any specific velocity-based distance (VBD) as the input to ACWR. Furthermore, no studies were identified that have investigated the interaction effects of the input with the coupling and averaging methods or acute and chronic time frames of the computational model on ACWR values.

Murray et al. investigated differences in ACWR calculation and injury risk between models using rolling average (RA) and exponentially weight moving average (EWMA) methods (Nicholas B. Murray et al. 2016). The study included six inputs, five of which were VBDs, from Australian Football and computed coupled ACWRs with 7- and 28-day acute and chronic time frames, respectively. The results showed the averaging methods were significantly different when using a one-way analysis of variance, and ACWRs from the EWMA model were lower than those from the RA model for moderate to very high ACWR ranges when using a logistic regression analysis. However, input and averaging method differences were only discussed in isolation and in relation to between-model variances within sections of injury likelihood curves, and their interactions were not included. While the objective of the study was to determine if differences existed between RA and EWMA models, interaction effects with other components on ACWR were not considered.

Gabbett et al. investigated ACWRs with coupled and not coupled methods (Gabbett et al. 2019). ACWRs were computed with 1-week and 4-week acute and chronic time frames, respectively. The study did not include a VBD for the input and did not specify the averaging method used. However, coupled and uncoupled ACWRs were shown to have a quadratic relationship with a R^2 value of 0.9973. The study did not assess the effect of coupling method on ACWR, but it suggested either method could be used if the ACWRs were interpreted based on criteria specific to the method. While the purpose of the study was to examine the association between coupled and uncoupled ACWRs and injury risk, the study did not consider interaction effects with other components on ACWR.

Carey et al. investigated ACWRs with different acute and chronic time frames (Carey et al. 2017). The study computed 56 ACWRs for six inputs, three of which were VBDs, using RA and coupled methods. Acute time frames were 2, 3, 4, 5, 6, 7, 8, and 9 days. Chronic time frames were 14, 18, 21, 24, 28, 32, and 35 days. The study concluded ACWRs computed using moderate-intensity running with a 3- or 6-day acute time frame with a 21- or 28-day chronic time frame were most associated with injury risk with respect to the data used, and it suggested the selection of acute and chronic time frames may be related to the training and competition schedule. While the aim of the study was to investigate effects on injury likelihood, the effects of acute and chronic time frames on ACWR were not investigated. The methods of the study also fixed the averaging and coupling method with a proposed daily ACWR formula and subsequently did not include their interaction effects with other components.

Specific Aims

Due to the inconclusive results regarding how best to calculate ACWR (Andrade et al. 2020) and adapt models to specific applications (Sampson, Fullagar, and Murray 2017); components should be evaluated within the contextual needs of a sport organization prior to their integration into an IMS. The purpose of this study was to investigate the effects of input, averaging method, coupling method, acute time frame, and chronic time frame on ACWR. The results establish a component hierarchy, which indicates component redundancies, that informs methodological decisions regarding the practical application of ACWR and subsequent analyses, such as injury likelihood and the accuracy, sensitivity, and specificity of an IMS.

The specific aims of this chapter were:

1. Determine if input (i.e., velocity-based distances) had a main effect or interaction effect with averaging method, coupling method, acute time frame, and/or chronic time frame on ACWR.
    - *Hypothesis: The null hypothesis was input did not have a main effect on ACWR, and the alternate hypothesis was input had a main effect.*
    - *Hypothesis: The null hypothesis was input did not have an interaction effect on ACWR, and the alternate hypothesis was input had an interaction effect.*
    - *Key Question: If a null hypothesis was rejected, which input levels had a not different effect on ACWR?*
    - *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different input levels on ACWR?*
2. Determine if averaging method (i.e., RA and EWMA) had a main effect or interaction effect with input, coupling method, acute time frame, and/or chronic time frame on ACWR.

- *Hypothesis: The null hypothesis was averaging method did not have a main effect on ACWR, and the alternate hypothesis was averaging method had a main effect.*
- *Hypothesis: The null hypothesis was averaging method did not have an interaction effect on ACWR, and the alternate hypothesis was averaging method had an interaction effect.*
- *Key Question: If a null hypothesis was rejected, which levels within averaging method had a not different effect on ACWR?*
- *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different averaging method levels on ACWR?*

3. Determine if coupling method (i.e., coupled and not coupled) had a main effect or interaction effect with input, averaging method, acute time frame, and/or chronic time frame on ACWR.

    - *Hypothesis: The null hypothesis was coupling method did not have a main effect on ACWR, and the alternate hypothesis was coupling method had a main effect.*
    - *Hypothesis: The null hypothesis was coupling method did not have an interaction effect on ACWR, and the alternate hypothesis was coupling method had an interaction effect.*
    - *Key Question: If a null hypothesis was rejected, which levels within coupling method had a not different effect on ACWR?*

- *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different coupling method levels on ACWR?*

4. Determine if acute time frame (i.e., 3-14 days) had a main effect or interaction effect with input, averaging method, coupling method, and/or chronic time frame effect on ACWR.
    - *Hypothesis: The null hypothesis was acute time frame did not have a main effect on ACWR, and the alternate hypothesis was acute time frame had a main effect.*
    - *Hypothesis: The null hypothesis was acute time frame did not have an interaction effect on ACWR, and the alternate hypothesis was acute time frame had an interaction effect.*
    - *Key Question: If a null hypothesis was rejected, which levels within acute time frame had a not different effect on ACWR?*
    - *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different acute time frame levels on ACWR?*
5. Determine if chronic time frame (i.e., 2-8 weeks) had a main effect or interaction effect with input, averaging method, coupling method, and/or acute time frame on ACWR.
    - *Hypothesis: The null hypothesis was chronic time frame did not have a main effect on ACWR, and the alternate hypothesis was chronic time frame had a main effect.*

- *Hypothesis: The null hypothesis was chronic time frame did not have an interaction effect on ACWR, and the alternate hypothesis was chronic time frame had an interaction effect.*
- *Key Question: If a null hypothesis was rejected, which levels within chronic time frame had a not different effect on ACWR?*
- *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different chronic time frame levels on ACWR?*

Methodology

This study was approved by the University of Louisville Internal Review Board. Written informed consent was obtained from each participant, when possible. Written informed consent was waived by the review board when its acquisition was not practically obtainable (i.e. subjects were no longer affiliated with the respective organization).

Subjects

Female student-athletes on the University of Louisville field hockey team during the 2017-18 to 2022-23 pre-seasons, in-seasons, and post-seasons were invited to participate as subjects. There were 55 subjects included in this study.

Data Collection

Retrospective VBDs from all training and competition activities of each subject during their respective pre-seasons, in-seasons, and post-seasons were included. Data from the 2020-21 season was excluded due to events associated with COVID-19.

Optimeye devices (Catapult Sports, Melbourne, Australia) were used during the 2017-18 to 2019-20 seasons, and Vector devices (Catapult Sports, Melbourne, Australia) were used during the 2021-22 and 2022-23 seasons. Session metrics were quantified using the OpenField Console (Catapult Sports, Melbourne, Australia) and represented the accumulation of a respective metric within active periods and rotations, established by a sport practitioner live or retroactively, across the activity. The session metrics consisted of the distances accumulated within eight separate velocity bands. The absolute velocity bands used by University of Louisville Athletics for female athletes were: less than 0.10 m/s for velocity band 1, 0.10 to less than 1.70 m/s for velocity band 2, 1.70 to less than 3.00 m/s for velocity band 3, 3.00 to less than 4.00 m/s for velocity band 4, 4.00 to less than 5.00 m/s for velocity band 5, 5.00 to less than 6.00 m/s for velocity band 6, 6.00 to less than 7.00 m/s for velocity band 7, 7.00 m/s and greater for velocity band 8.

Data Processing

Acute:chronic workload ratios were determined for each input from each subject within each session using RA and EWMA methods with coupled and not coupled approaches using acute time frames of 3, 5, 7, 10, and 14 days and chronic time frames of 14, 21, 28, 35, 42, 49, and 56 days. Acute:chronic workload ratios were calculated using

$$ACWR = \frac{W_a}{W_c} \tag{3}$$

where W_a was the acute workload and W_c was the chronic workload (Hulin et al. 2013). Inputs consisted of thirty-six VBDs determined by sequentially adding together the distances accumulated within each velocity band (e.g., distance from velocity band 1, distance from velocity bands 2-5, distance from velocity bands 1-8, etc.). Acute and chronic workloads were calculated for the EWMA method using

$$EWMA_s = [L_s \quad L_{s-1} \quad L_{s-2} \quad \cdots \quad L_{s-i}] \cdot \begin{bmatrix} W_s \\ W_{s-1} \\ W_{s-2} \\ \vdots \\ W_{s-i} \end{bmatrix} \tag{4}$$

where L was the load of the session with respect to session s, i was an index ranging from 0 to N-1, N was the respective acute or chronic time frame, and W was the weighting factor for the corresponding load. Each weighting factor was calculated using

$$W_{s-i} = \lambda(1-\lambda)^i \tag{5}$$

where λ was the degree of decay from Equation (2. Acute and chronic workloads were calculated for the RA method using

$$RA_s = [L_s \quad L_{s-1} \quad L_{s-2} \quad \cdots \quad L_{s-i}] \cdot \begin{bmatrix} 1 \\ 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \cdot \frac{1}{N}. \tag{6}$$

For RA or EWMA cases where the chronic workload was not coupled with the acute workload, the loads within the chronic workload that were associated with the acute workload were replaced with zeros and N within the chronic workload was the difference between the respective chronic and acute time frame. The acute and chronic workloads presented the product of 1xN and Nx1 matrices that resulted in scalar values, which indicated the ACWR of one subject for a given session.

At the beginning of each season, ACWRs where the number of sessions was less than the number of days in the chronic time frame were excluded due to the initialization phase of ACWR computations. Any ACWR configuration where the number of sessions within the acute time frame was greater than or equal to the number of sessions within the chronic time frame (e.g., configurations with a 14-day acute and chronic time frame) were also excluded. Based on the data processing steps, there were 128 unique ACWR computation configurations used with each input resulting in 4608 total ACWR groups. Outliers within each group were identified using the interquartile range method and removed.

The remaining ACWRs within each group were interpolated to values between 0% and 100% of their respective range due to absolute ACWRs potentially impacting the means and dispersions within an analysis of variance (ANOVA). For example, coupled ACWRs with a 7-day acute time frame and 21-day chronic time frame could theoretically range from 0 to 3, while coupled ACWRs with a 3-day acute time frame and 42-day chronic time frame could theoretically range from 0 to 14. Consequently, different effects could be observed between absolute and relative ACWRs, but the differences would not have any practical significance when the absolute and relative ACWRs from the same configuration are evaluated with equivalent criteria.

Statistical Analysis

The use of a desktop computer, rather than a supercomputing mainframe, necessitated the statistical analysis to be conducted in a two-stage approach using Minitab 12.4.1 (Minitab, LLC, State College, Pennsylvania). For the first stage, a general linear mixed model (GLMM) ANOVA was used to identify main effects of each factor (i.e., model input, averaging method, coupling method, acute time frame, and chronic time frame) on ACWR. Model input had thirty-six VBD levels. Averaging method had two levels of RA and EWMA. Coupling method had two levels of coupled and not coupled. Acute time frame had five levels of 3, 5, 7, 10, and 14 days. Chronic time frame had seven levels of 14, 21, 28, 35, 42, 49, and 56 days. Subject was included as a blocking factor to control for inherent inter-subject variability. The response variable was ACWR expressed as a percentage of the respective group distribution, and only main effects were included in the model. Factors with a p-value less than 0.05 were considered to be statistically significant and included in the Tukey test, which was used to identify levels within each factor that were not statistically different. After the Tukey test was performed, levels within each factor that were not statistically different as other levels were removed from the dataset for the second GLMM ANOVA. For the second stage, a GLMM ANOVA was used to determine the interaction effects between factors on ACWR. All interactions between factors with a statistically significant main effect were included in the model. Interaction effects with a p-value less than 0.05 were considered to be statistically significant. Factorial plots were then generated for significant two-factor interactions to assess whether their impact on ACWR depended on the level of one of the factors.

Results

Main Effects and Tukey Test

Input, averaging method, coupling method, acute time frame, and chronic time frame each had a statistically significant main effect on ACWR (p-values < 0.001). The null hypothesis associated with the main effect of each factor was rejected, and the alternate hypothesis was accepted. All five factors were included in the subsequent Tukey test. The Tukey test results for input, averaging method, coupling method, acute time frame, and chronic time frame following the main effects analysis are shown in Tables 1-5, respectively.

Table 1. Tukey test results for input in association with ACWR.

Input	n	Mean (%)	Grouping										
VBD bands 1-4	572416	49.458	A										
VBD bands 1-6	572627	49.431	A	B									
VBD bands 2-4	572367	49.427	A	B									
VBD bands 2-5	572441	49.414	A	B									
VBD bands 2-3	571860	49.404	A	B									
VBD bands 2-8	572553	49.399	A	B									
VBD bands 1-5	572492	49.398	A	B									
VBD bands 1-8	572607	49.394	A	B									
VBD bands 2-7	572653	49.391	A	B									
VBD bands 1-3	571912	49.390	A	B									
VBD bands 2-6	572580	49.386	A	B	C								
VBD bands 1-7	572699	49.386	A	B	C								
VBD band 4	574376	49.383	A	B	C								
VBD bands 3-4	572795	49.379	A	B	C								
VBD band 2	573615	49.372	A	B	C								
VBD bands 3-7	573343	49.359	A	B	C	D							
VBD bands 3-8	573236	49.358	A	B	C	D							
VBD bands 3-5	573168	49.356	A	B	C	D							
VBD bands 3-6	573295	49.339	A	B	C	D	E						
VBD bands 1-2	573636	49.324		B	C	D	E						
VBD bands 4-5	574847	49.318		B	C	D	E						
VBD band 3	571407	49.306		B	C	D	E						
VBD bands 4-6	574756	49.256			C	D	E						
VBD bands 4-8	574752	49.238				D	E						
VBD bands 4-7	574887	49.220					E						
VBD band 1	572464	49.065						F					
VBD band 5	572351	48.954						F					
VBD bands 5-6	571847	48.717							G				
VBD bands 5-7	572217	48.619							G				
VBD bands 5-8	572123	48.611							G				
VBD band 6	568961	46.509								H			
VBD bands 6-7	569810	46.027									I		
VBD bands 6-8	569837	46.012									I		
VBD band 7	557327	35.390										J	
VBD bands 7-8	557203	35.360										J	
VBD band 8	317824	18.494											K

Means that do not share a letter were significantly different.

Table 2. Tukey test results for averaging method in association with ACWR.

Averaging Method	n	Mean (%)	Grouping	
RA	10158467	47.495	A	
EWMA	10170817	47.274		B

Means that do not share a letter were significantly different.

Table 3. Tukey test results for coupling method in association with ACWR.

Coupling Method	n	Mean (%)	Grouping	
Coupled	10211750	47.943	A	
Not coupled	10117534	46.826		B

Means that do not share a letter were significantly different.

Table 4. Tukey test results for acute time frame in association with ACWR.

Acute Time Frame (days)	n	Mean (%)	Grouping				
14	2881176	48.456	A				
10	3693835	48.051		B			
7	4551907	47.749			C		
5	4593338	47.140				D	
3	4609028	45.527					E

Means that do not share a letter were significantly different.

Table 5. Tukey test results for chronic time frame in association with ACWR.

Chronic Time Frame (days)	n	Mean (%)	Grouping				
21	3233263	47.561	A				
14	2640879	47.510		B			
28	3643853	47.484		B			
35	3270887	47.394			C		
42	2900689	47.327				D	
56	2126754	47.233					E
49	2512959	47.184					E

Means that do not share a letter were significantly different.

Seven of the thirty-six inputs were statistically different, and the levels were reduced to the VBDs from velocity bands 3-6, band 5, bands 5-8, band 6, bands 6-8, bands 7-8, and band 8. Five of the seven chronic time frames were statistically different, and the levels were reduced to 21, 28, 35, 42, and 49 days. All the levels within averaging method, coupling method, and acute time frame were statistically different; and none of the levels within those factors were removed for the interaction effects analysis.

Model input generally decreased ACWRs as the VBDs included fewer velocity bands or were associated with higher velocities. Greater ACWRs were produced when using the RA method compared to EWMA as well as when the acute and chronic workload were coupled compared to not coupled. There was an increasing effect on ACWR as the duration of the acute time frame increased and a decreasing effect on ACWR as the duration of the chronic time frame increased.

Interaction Effects and Factorial Plots

Input, averaging method, coupling method, acute time frame, and chronic time frame each had a statistically significant 2-, 3-, and 4-factor interaction effect on ACWR (p-values < 0.001). Therefore, the null hypothesis associated with the interaction effect of each factor was rejected, and the alternate hypothesis was accepted.

The factorial plots in Figures 1 and 2 show interactions where the effect of one factor was determined to be independent of the level within another factor, while the factorial plots in Figures 3-5 show interactions where the effect of one factor was determined to be dependent of the level within another factor. The dependencies between interacting factors are shown in Table 6.

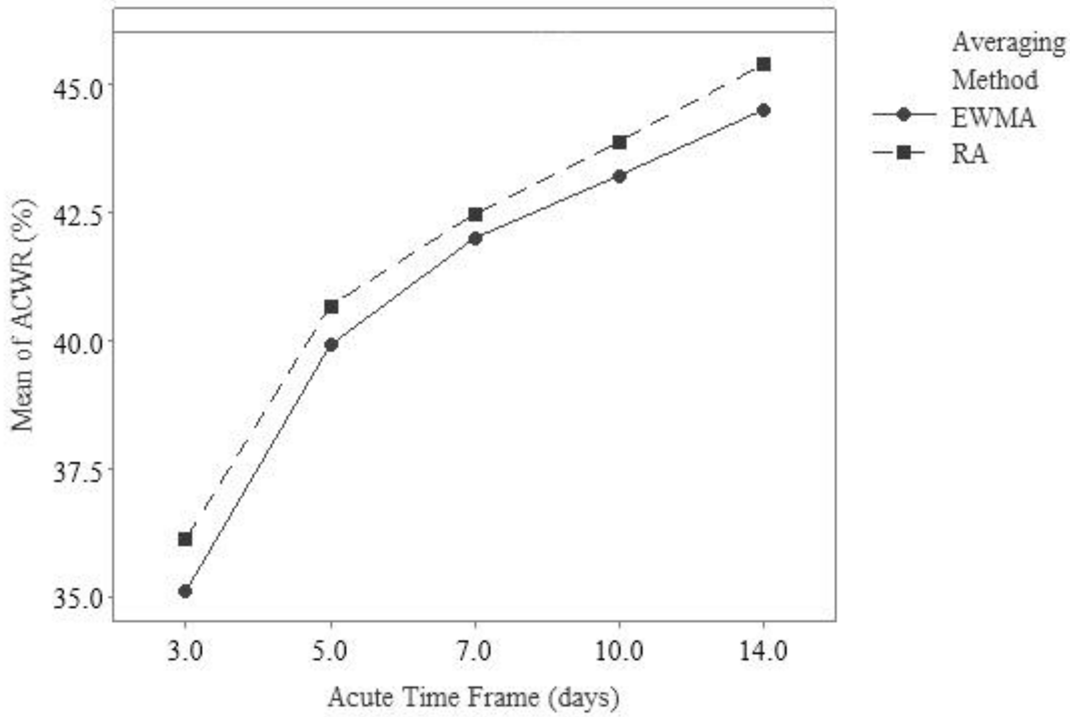

Figure 1. Two-factor factorial plot for the interaction effect between acute time frame and averaging method on mean ACWR.

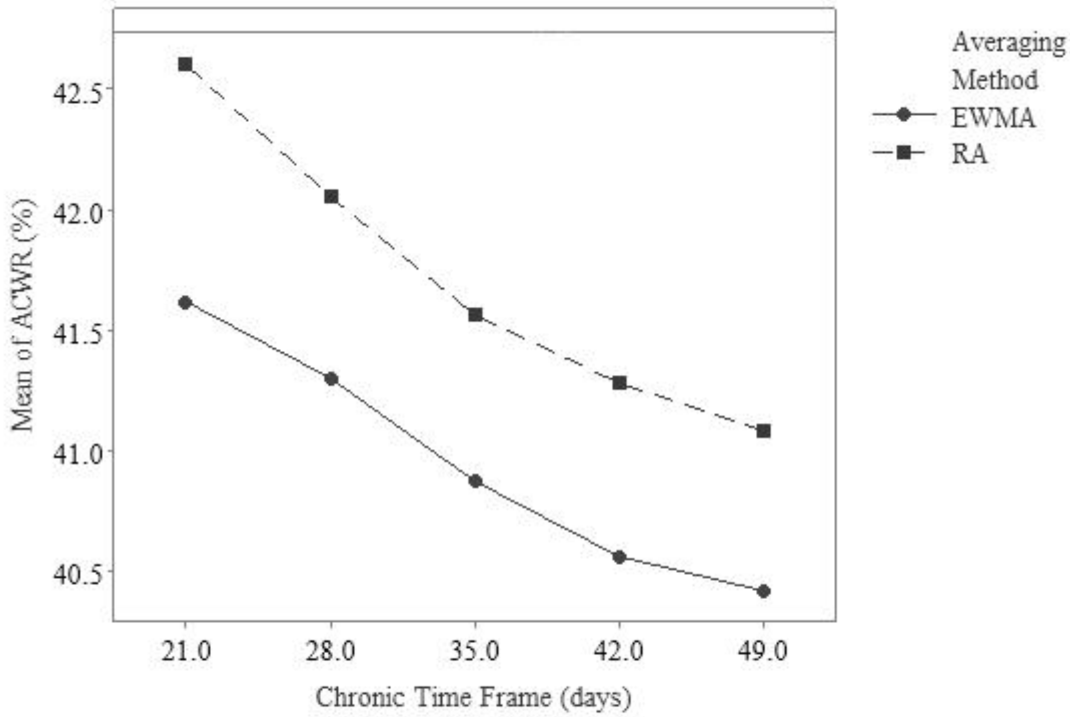

Figure 2. Two-factor factorial plot for the interaction effect between chronic time frame and averaging method on mean ACWR.

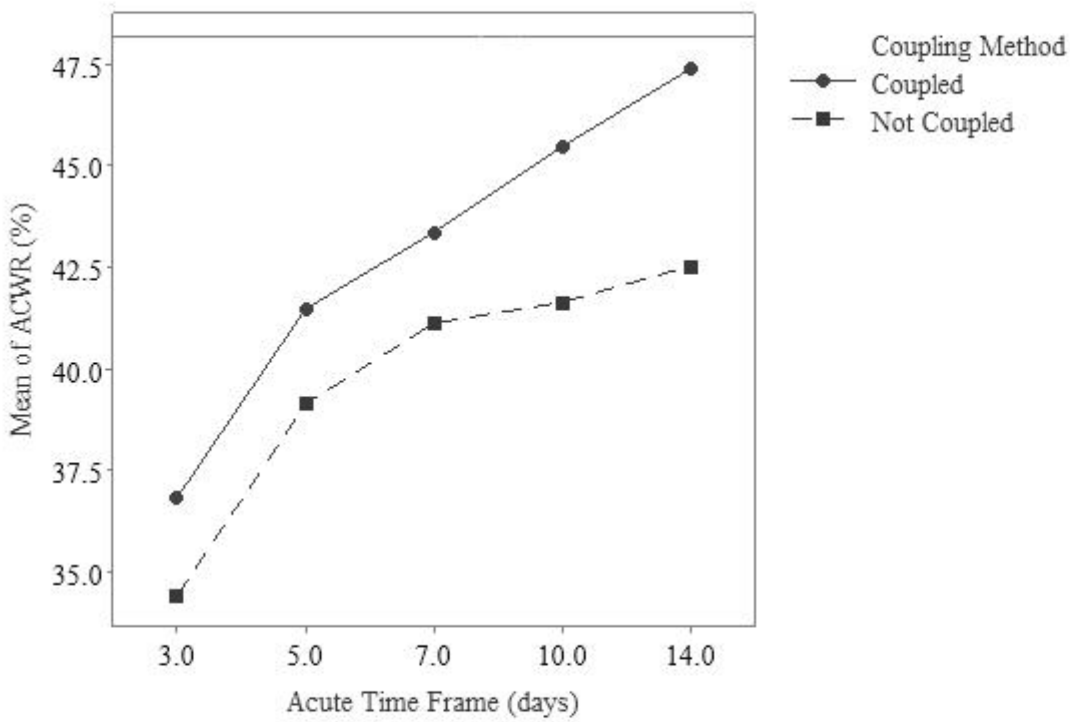

Figure 3. Two-factor factorial plot for the interaction effect between acute time frame and coupling method on mean ACWR.

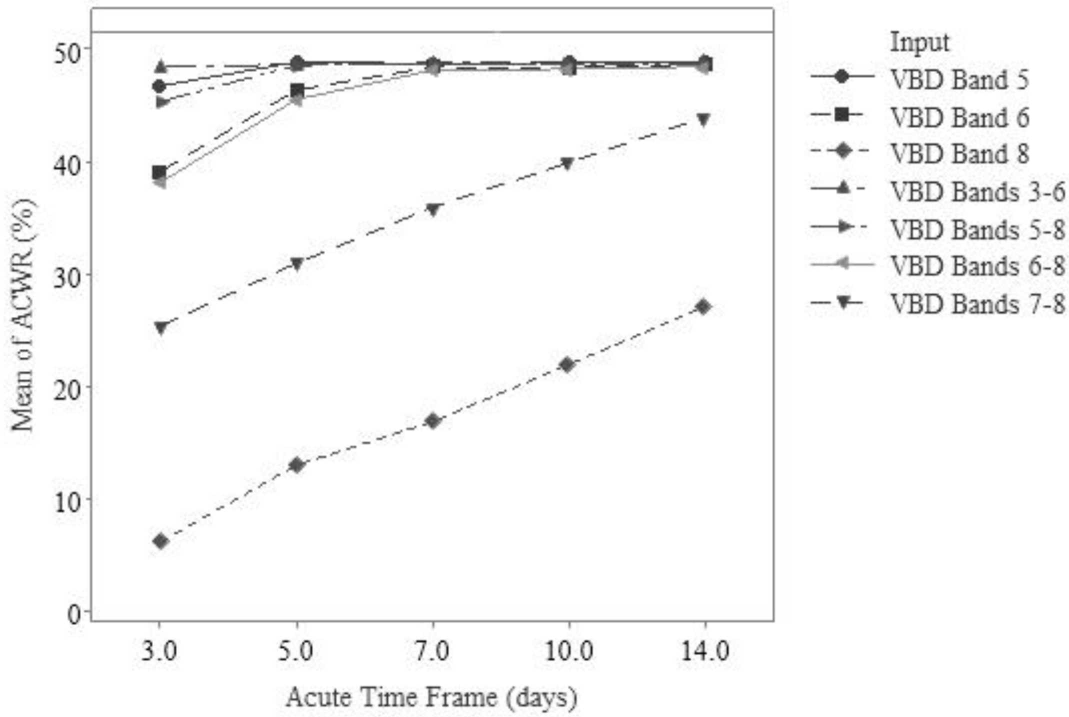

Figure 4. Two-factor factorial plot for the interaction effect between acute time frame and input on mean ACWR.

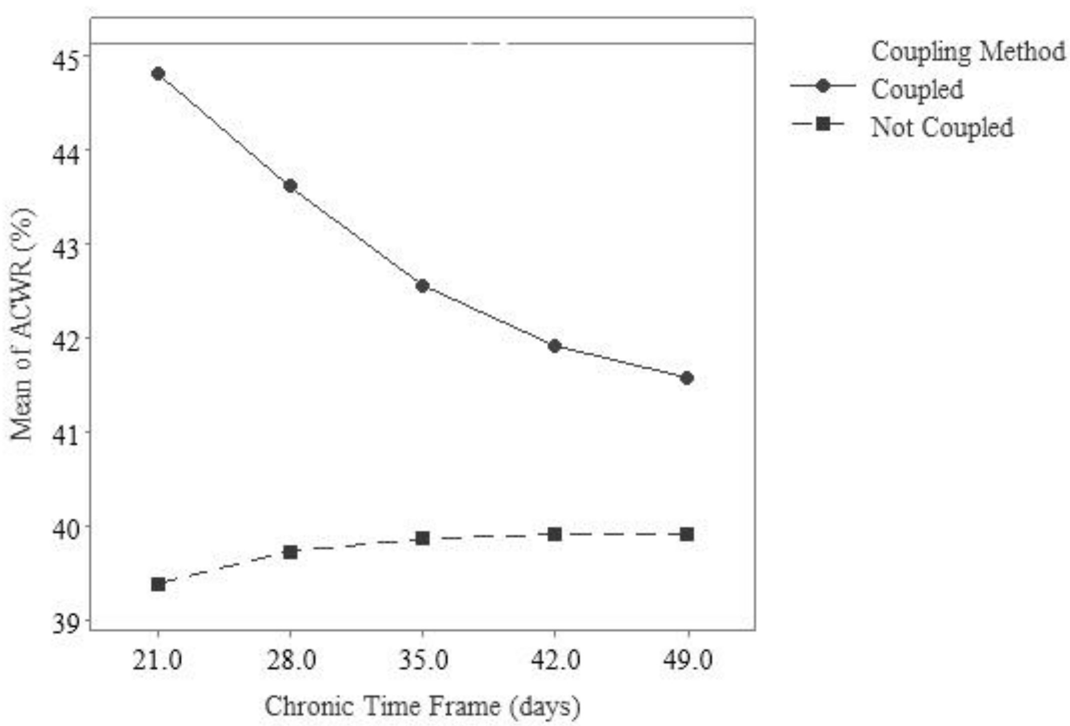

Figure 5. Two-factor factorial plot for the interaction effect between chronic time frame and coupling method on mean ACWR.

Table 6. The dependency of factor levels within two-factor interactions for the interaction effect of given factors on mean ACWR. Factor dependencies were independent (I), dependent (D), or unable to be determined by Minitab (X).

	Input	Averaging Method	Coupling Method	Acute Time Frame	Chronic Time Frame
Input	-	I	D	D	D
Averaging Method	I	-	I	I	I
Coupling Method	D	I	-	D	D
Acute Time Frame	D	I	D	-	X
Chronic Time Frame	D	I	D	X	-

Input and coupling method were each dependent on the level within all other factors except averaging method. Acute and chronic time frame were each dependent on the level within input and coupling method. Averaging method was independent of the level within all other factors. The factorial plot for the effect between acute and chronic time frame on ACWR was indeterminable by Minitab.

Discussion

Main and Interaction Effects

Current recommendations in the literature demonstrate selecting ACWR methodologies while considering components in isolation from others. When evaluating the components within this study in isolation, the statistically significant differences between the reduced levels would likely not have any practical significance, and the results would suggest simply including ACWR in an application, regardless of the methods used, would be sufficient for practitioners when ACWRs between different configurations are interpreted with equivalent criteria. However, when considering the interactions between ACWR components, there are compounding effects that could have a practical significance. For example, the differences between mean ACWRs within coupling method and chronic time frame were 1.12% and 0.38%, respectively. From Figure 5, mean ACWR could vary by more than 5% depending on the specific combination of those two factors used, and the interactions between three, four, and five factors are likely to further compound the differences between ACWRs. Consequently, the methodological differences between studies in the literature may be contributing to the inconclusive implications associated with ACWR because those studies do not consider the impact of all factors interacting together.

ACWR Component Interactions and Hierarchy

The computation of ACWR includes a complex interaction between the required components. Coupling method has been recognized to impact the chronic workload by including or excluding input data associated with the acute workload (Lolli et al. 2019). When ACWR methods are not coupled, the amount of input data removed is dictated by the duration of the acute time frame, and the acute time frame may be influenced by an optimal ratio with the chronic time frame (Delecroix et al. 2018; Fanchini et al. 2018; McCall, Dupont, and Ekstrand 2018). Furthermore, when methods include EWMA averaging with acute and chronic workloads that are not coupled, the effects of the higher weights linked to the removed input data are also removed. When the RA averaging method is used, uncoupling does not impact weighting due to the method consisting of constant weights. When the interactions between all components are considered, it is unclear which components have a greater impact on ACWR values than others.

The results of this study suggest the methodologies associated with ACWR at a computational level should be developed in a hierarchical order: 1) model input, 2) acute time frame, 3) coupling method, 4) chronic time frame, and 5) averaging method. The input selected contributed to more ACWR variation than other components and influenced the effects of acute time frame, coupling method, and chronic time frame. Of the components dependent on input, acute time frame contributed to more ACWR variation than coupling method, and coupling method contributed to more ACWR variation than chronic time frame. Averaging method had the smallest impact on ACWR variation and was independent of the other components.

In addition to the effects between ACWR groups being caused by the methodologies used to compute their values, differing datasets may also produce different results. However, the analytical processes used in this study can be replicated by practitioners to guide the development of an ACWR-based IMS within the context of their own environment.

Limitations

The statistical differences between inputs may be influenced by the use of absolute velocity bands, the ranges associated with those velocity bands, and only considering velocity to discriminate between distances. Depending on the subject, distances accumulated within higher bands may be influenced by the subject's physical limitations, which may be mitigated by the use of relative or alternative absolute velocity bands. Velocity bands have been defined using various analytical and physiological approaches, but a standard method has yet to be established (Gualtieri et al. 2023).

Furthermore, establishing distances based on direction, velocity, and acceleration may result in more levels that are statistically different at lower velocities.

The dependencies and thus the hierarchy of ACWR components were affected by the subjective interpretation of the two-factor factorial plots. Dependencies could be established by obtaining and comparing interpretations from additional sources. Hierarchies may alternatively be established using data science techniques; though, the technique must be able to assess multiple levels within the various factors.

Conclusions

When determining ACWR methodologies, a configuration should not be selected without considering the interactions between its components. Practitioners should reduce methodologies from the literature and establish a hierarchy that guides the development of an ACWR-based injury mitigation strategy based on the needs of their specific environment. Alternately, the determination of model input should be prioritized over the components within the ACWR model. Then, models should be developed by selecting the methods for acute time frame, coupling method, chronic time frame, and then averaging method. At some point within the development progression, the specific level used for a component may not provide a practical benefit over other levels.

CHAPTER 3

EFFECTS OF ACUTE:CHRONIC WORKLOAD RATIO METHODOLOGIES ON INJURY LIKELIHOOD IN WOMEN'S COLLEGIATE FIELD HOCKEY

Background and Significance

Many studies in the literature investigate the acute:chronic workload ratio (ACWR) with injury likelihood to develop strategies for mitigating the injury risk associated with sport-related activities. A strategy demonstrated by the literature is to plan and monitor workloads within an ACWR range associated with lower injury risk. The ACWR range is established by an injury likelihood profile, and practitioners are encouraged to adapt their methods to the competition schedule and periodization of a sport or athlete (Andrade et al. 2020). This strategy requires an injury definition and injury lag period in addition to the methodologies required to compute ACWR (i.e., input, averaging method, coupling method, acute time frame, and chronic time frame). It is unclear how the methodological variations, within and between components, affect the utility of the strategy, where the methodological variation may impact the profile, thus the ACWR values used to plan and manage workloads.

Several different injury definitions and lag periods have been utilized within the ACWR literature (Griffin et al. 2020; Andrade et al. 2020). Some definitions include all instances reported by athletes to medical staff while others consider mixed criteria, such as non-contact, lower body, and time-loss injuries. Time-loss injuries further discriminate between full, modified, and missed participation within training sessions and/or matches. The injury lag period represents the time frame following an ACWR value where an athlete is predisposed to higher injury risk, and spikes in training and competition loads have been shown to expose an athlete to higher injury risk for up to 3-4 weeks following a spike (Stares et al. 2018). Injury lag period seems to have an effect on injury risk and can be adapted to address the specificities of a sport and injury type (Carey et al. 2017; Orchard et al. 2015).

The effects of methodological components on ACWR were previously investigated in Chapter 2. The results showed that interactions between ACWR components had compounding effects that would impact how ACWR is used and suggested injury mitigation strategies using ACWR should be developed in a hierarchical order. Because injury likelihood profiles are based on the relationship between ACWR and injury likelihood, where injury likelihood is also determined using ACWR, the effects of the various methods used may propagate into values that establish the profile; causing it to shift or change shape. Consequently, the propagating effects may prevent general ACWR ranges associated with low injury risk that are found in the literature from being applied by a sport organization.

Specific Aims

Understanding the effects of components required to evaluate injury likelihood will direct a sport organization to which factors have practical utility for mitigating injuries. The effects of injury definition and injury lag periods may have a greater impact on injury likelihood than ACWR and its respective methods. Simply including ACWR, irrespective of the input and computational methods, within an injury mitigation strategy may be sufficient. Conversely, a strategy may require tailored ACWR methodologies to be effective. The purpose of this study was to investigate the main and interaction effects of injury definition, injury lag period, input, averaging method, coupling method, acute time frame, and chronic time frame on injury likelihood. The results provide insight towards the significance of each component relative to other components when developing an injury mitigation strategy using injury likelihood.

The specific aims of this chapter were:

1. Determine if input (i.e., velocity-based distances) had a main effect or interaction effect with averaging method, coupling method, acute time frame, chronic time frame, injury definition, and/or injury lag period on injury likelihood.
    - *Hypothesis: The null hypothesis was input did not have a main effect on injury likelihood, and the alternate hypothesis was input had a main effect.*
    - *Hypothesis: The null hypothesis was input did not have an interaction effect on injury likelihood, and the alternate hypothesis was input had an interaction effect.*
    - *Key Question: If a null hypothesis was rejected, which input levels had a not different effect on injury likelihood?*
    - *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different input levels on injury likelihood?*
2. Determine if averaging method (i.e., rolling and exponentially weighted moving average) had a main effect or interaction effect with input, coupling method, acute

time frame, chronic time frame, injury definition, and/or injury lag period on injury likelihood.

- *Hypothesis: The null hypothesis was averaging method did not have a main effect on injury likelihood, and the alternate hypothesis was averaging method had a main effect.*
- *Hypothesis: The null hypothesis was averaging method did not have an interaction effect on injury likelihood, and the alternate hypothesis was averaging method had an interaction effect.*
- *Key Question: If a null hypothesis was rejected, which levels within averaging method had a not different effect on injury likelihood?*
- *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different averaging method levels on injury likelihood?*

3. Determine if coupling method (i.e., coupled and not coupled) had a main effect or interaction effect with input, averaging method, acute time frame, chronic time frame, injury definition, and/or injury lag period on injury likelihood.
    - *Hypothesis: The null hypothesis was coupling method did not have a main effect on injury likelihood, and the alternate hypothesis was coupling method had a main effect.*
    - *Hypothesis: The null hypothesis was coupling method did not have an interaction effect on injury likelihood, and the alternate hypothesis was coupling method had an interaction effect.*

- *Key Question: If a null hypothesis was rejected, which levels within coupling method had a not different effect on injury likelihood?*
- *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different coupling method levels on injury likelihood?*

4. Determine if acute time frame (i.e., 3-14 days) had a main effect or interaction effect with input, averaging method, coupling method, chronic time frame, injury definition, and/or injury lag period on injury likelihood.
    - *Hypothesis: The null hypothesis was acute time frame did not have a main effect on injury likelihood, and the alternate hypothesis was acute time frame had a main effect.*
    - *Hypothesis: The null hypothesis was acute time frame did not have an interaction effect on injury likelihood, and the alternate hypothesis was acute time frame had an interaction effect.*
    - *Key Question: If a null hypothesis was rejected, which levels within acute time frame had a not different effect on injury likelihood?*
    - *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different acute time frame levels on injury likelihood?*
5. Determine if chronic time frame (i.e., 21-49 days) had a main effect or interaction effect with input, averaging method, coupling method, acute time frame, injury definition, and/or injury lag period on injury likelihood.

- *Hypothesis: The null hypothesis was chronic time frame did not have a main effect on injury likelihood, and the alternate hypothesis was chronic time frame had a main effect.*
- *Hypothesis: The null hypothesis was chronic time frame did not have an interaction effect on injury likelihood, and the alternate hypothesis was chronic time frame had an interaction effect.*
- *Key Question: If a null hypothesis was rejected, which levels within chronic time frame had a not different effect on injury likelihood?*
- *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different chronic time frame levels on injury likelihood?*

6. Determine if injury definition (i.e., general and specific) had a main effect or interaction effect with input, averaging method, coupling method, acute time frame, chronic time frame, and/or injury lag period on injury likelihood.
    - *Hypothesis: The null hypothesis was injury definition did not have a main effect on injury likelihood, and the alternate hypothesis was injury definition had a main effect.*
    - *Hypothesis: The null hypothesis was injury definition did not have an interaction effect on injury likelihood, and the alternate hypothesis was injury definition had an interaction effect.*
    - *Key Question: If a null hypothesis was rejected, which injury definition levels had a not different effect on injury likelihood?*

- *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different injury definition levels on injury likelihood?*

7. Determine if injury lag period (i.e., 0-28 days) had a main effect or interaction effect with input, averaging method, coupling method, acute time frame, chronic time frame, and/or injury definition on injury likelihood.
    - *Hypothesis: The null hypothesis was injury lag period did not have a main effect on injury likelihood, and the alternate hypothesis was injury lag period had a main effect.*
    - *Hypothesis: The null hypothesis was injury lag period did not have an interaction effect on injury likelihood, and the alternate hypothesis was injury lag period had an interaction effect.*
    - *Key Question: If a null hypothesis was rejected, which injury lag period levels had a not different effect on injury likelihood?*
    - *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different injury lag period levels on injury likelihood?*
8. Compare the effects of input, averaging method, coupling method, acute time frame, and chronic time frame and their respective levels between ACWR and injury likelihood.
    - *Key Question: Were the input factor and factor level effects consistent between ACWR and injury likelihood analyses?*

- *Key Question: Were the averaging method factor and factor level effects consistent between ACWR and injury likelihood analyses?*
- *Key Question: Were the coupling method factor and factor level effects consistent between ACWR and injury likelihood analyses?*
- *Key Question: Were the acute time frame factor and factor level effects consistent between ACWR and injury likelihood analyses?*
- *Key Question: Were the chronic time frame factor and factor level effects consistent between ACWR and injury likelihood analyses?*

Methodology

This study was approved by the University of Louisville Internal Review Board. Written informed consent was obtained from each participant, when possible. Written informed consent was waived by the review board when its acquisition was not practically obtainable (i.e. subjects were no longer affiliated with the respective organization).

Subjects

Female student-athletes on the University of Louisville field hockey team during the 2017-18 to 2022-23 pre-seasons, in-seasons, and post-seasons were invited to participate as subjects. There were 55 subjects included in this study.

Data Collection

ACWRs computed in Chapter 2 that had factors and factor levels with statistically significant and different effects on ACWR were used. Configurations with significant and different effects included velocity-based distances (VBDs) from velocity bands 3-6, band

5, bands 5-8, band 6, bands 6-8, bands 7-8, and band 8; rolling average (RA) and exponentially weight moving average (EWMA) averaging methods; coupled and not coupled coupling methods; acute time frames of 3, 5, 7, 10, and 14 days; and chronic time frames of 21, 28, 35, 42, and 49 days. Each ACWR was expressed as a value between 0 and 100% of the respective group range, and outliers within each group were removed using the interquartile range method. There were 672 ACWR groups included.

Sport-related injury data recorded by the team athletic trainer was also used. Injury data collected during the 2018-19 to 2022-23 pre- to post-seasons was included. However, data from the 2020-21 season was excluded due to events associated with COVID-19. There were 158 injury instances included.

Data Processing

For each ACWR group, the likelihood of injury associated with an ACWR was determined using an injury likelihood profile. Injury likelihood profiles were developed using ACWRs from the respective input, computational, and injury criterion configuration in addition to a standardized binning process and interpolation method.

The injury criterion determined if an ACWR was associated with an injury based on an injury definition and lag period. If the definition was satisfied within the lag period following the ACWR exposure, the ACWR was associated with an injury. If the definition was not satisfied within the lag period following the ACWR exposure, the ACWR was not associated with an injury. Two injury definitions were used based on practical outcomes: 1) the athletic trainer recorded a subject experienced a sport-related muscle, tendon, ligament, or bone injury in the lower body or torso; 2) the athletic trainer recorded a subject experienced a sport-related muscle, tendon, ligament, or bone injury in the lower body or torso, and the subject missed a training or competition session. Injury lag period durations consisted of 0, 3, 7, 10, 14, 21, and 28 days following an ACWR exposure.

The binning process was the initial step for establishing knots that were used to create a spline interpolation function for the injury likelihood profile. Each ACWR within the respective input and computational configuration was binned, where the splits between bins were determined using an optimal binning algorithm with a binary target from the OptBinning 0.17.3 Python package (Navas-Palencia 2022). Within the algorithm, ACWR was the discretized variable while the injury criterion with an injured or not injured outcome expressed as a 1 or 0, respectively, was the binary target variable. Within each bin, injury likelihood was the number of ACWR exposures associated with an injury relative to all ACWR exposures. The injury likelihood of and ACWR mid-point within each bin established the knot associated with the bin, and the knots from all bins were used to generate a cubic spline function that modeled the injury likelihood profile. The cubic spline interpolation function was created using the scipy 1.11.1 Python package. Due to there being two injury definitions and seven injury lag periods, fourteen profiles were created for each of the ACWR groups; resulting in 9408 injury likelihood groups.

Statistical Analysis

The use of a desktop computer, rather than a supercomputing mainframe, necessitated the statistical analysis to be conducted in a two-stage approach using Minitab 12.4.1 (Minitab, LLC, State College, Pennsylvania). For the first stage, a general linear mixed model (GLMM) ANOVA was used to identify main effects of each factor (i.e., input, averaging method, coupling method, acute time frame, chronic time frame, injury definition, and injury lag period) on injury likelihood. Input had seven VBD levels consisting of distances from velocity bands 3-6, band 5, bands 5-8, band 6, bands 6-8, bands 7-8, and band 8. Averaging method had two levels of RA and EWMA. Coupling method had two levels of coupled and not coupled. Acute time frame had five levels of 3, 5, 7, 10, and 14 days. Chronic time frame had five levels of 21, 28, 35, 42, and 49 days. Injury definition had two factor levels of general and specific definitions. Injury lag period had seven factor levels of 0, 3, 7, 10, 14, 21, and 28 days. Subject was included as a blocking factor to control for inherent inter-subject variability. Injury likelihood was the response variable, and only main effects were included in the model. Factors with a p-value less than 0.05 were considered to be statistically significant and included in the Tukey test, which was used to identify levels within each factor that were not statistically different. After the Tukey test was performed, levels within each factor that were not statistically different as other levels were removed from the dataset for the second GLMM ANOVA. For the second stage, a GLMM ANOVA was used to determine the interaction effects between factors on injury likelihood. Interactions between factors with a statistically significant main effect were included in the model, and the number of interacting factors was limited to three factors by Minitab. Interaction effects with a p-value less than 0.05 were considered to be statistically significant. Factorial plots were then generated for significant two-factor interactions to assess whether their impact on injury likelihood depended on the level of one of the factors.

Results

Main Effects and Tukey Test

Input, averaging method, coupling method, acute time frame, chronic time frame, injury definition, and injury lag period each had a statistically significant main effect on injury likelihood (p-values < 0.001). Therefore, the null hypothesis associated with the main effect of each factor was rejected, and the alternate hypothesis was accepted. All seven factors were included in the subsequent Tukey test.

The Tukey test results for input, averaging method, coupling method, acute time frame, and chronic time frame following the main effects analysis are shown in Tables 7-13, respectively.

Table 7. Tukey test results for input in association with injury likelihood.

Input	n	Mean (%)	Grouping				
VBD bands 7-8	4700430	9.556	A				
VBD band 6	4799046	9.412		B			
VBD bands 6-8	4810092	9.379		B			
VBD band 5	4835376	9.328		B	C		
VBD bands 5-8	4831778	9.262			C		
VBD bands 3-6	4859372	9.112				D	
VBD band 8	2603006	6.554					E

Means that do not share a letter were significantly different.

Table 8. Tukey test results for averaging method in association with injury likelihood.

Averaging Method	n	Mean (%)	Grouping	
RA	15696800	9.021	A	
EWMA	15742300	8.866		B

Means that do not share a letter were significantly different.

Table 9. Tukey test results for coupling method in association with injury likelihood.

Coupling Method	n	Mean (%)	Grouping	
Coupled	15905442	8.987	A	
Not coupled	15533658	8.900		B

Means that do not share a letter were significantly different.

Table 10. Tukey test results for acute time frame in association with injury likelihood.

Acute Time Frame (days)	n	Mean (%)	Grouping				
5	6635874	9.281	A				
7	6616470	9.100		B			
14	4970028	8.960			C		
3	6612900	8.741				D	
10	6603828	8.635					E

Means that do not share a letter were significantly different.

Table 11. Tukey test results for chronic time frame in association with injury likelihood.

Chronic Time Frame (days)	n	Mean (%)	Grouping				
28	7356328	9.332	A				
21	6498254	9.191		B			
35	6622714	8.831			C		
49	5100172	8.734				D	
42	5861632	8.629					E

Means that do not share a letter were significantly different.

Table 12. Tukey test results for injury definition in association with injury likelihood.

Definition	n	Mean (%)	Grouping	
General	15719550	17.067	A	
Specific	15719550	0.820		B

Means that do not share a letter were significantly different.

Table 13. Tukey test results for injury lag period in association with injury likelihood.

Lag Period (days)	n	Mean (%)	Grouping						
28	4491300	18.625	A						
21	4491300	15.157		B					
14	4491300	11.147			C				
10	4491300	8.158				D			
7	4491300	6.251					E		
3	4491300	2.900						F	
0	4491300	0.366							G

Means that do not share a letter were significantly different.

Four of the seven inputs were statistically different, and the levels were reduced to the VBDs from bands 7-8, band 5, bands 3-6, and band 8. All the levels within averaging method, coupling method, acute time frame, chronic time frame, injury definition, and injury lag period were statistically different; and none of the levels within those factors were removed for the interaction effects analysis.

Greater injury likelihoods occurred when using the RA method compared to EWMA, coupled workloads compared to not coupled, and the general definition compared to the specific definition. As the duration of the chronic time frame increased, injury likelihood generally decreased. There was an increasing effect on injury likelihood as injury lag period increased. The effect of changes in VBDs and acute time frames on injury likelihood was inconclusive.

Interaction Effects and Factorial Plots

Input, averaging method, coupling method, acute time frame, chronic time frame, injury definition, and injury lag period each had a statistically significant 2- and 3-factor interaction effect on injury likelihood (p-value < 0.001). Therefore, the null hypothesis associated with the interaction effect of each factor was rejected, and the alternate hypothesis was accepted.

The factorial plots in Figures 6 and 7 show interactions where the effect of one factor was determined to be independent of the level within another factor, while the factorial plots in Figures 8 and 9 show interactions where the effect of one factor was determined to be dependent of the level within another factor. The dependencies between interacting factors are shown in Table 14.

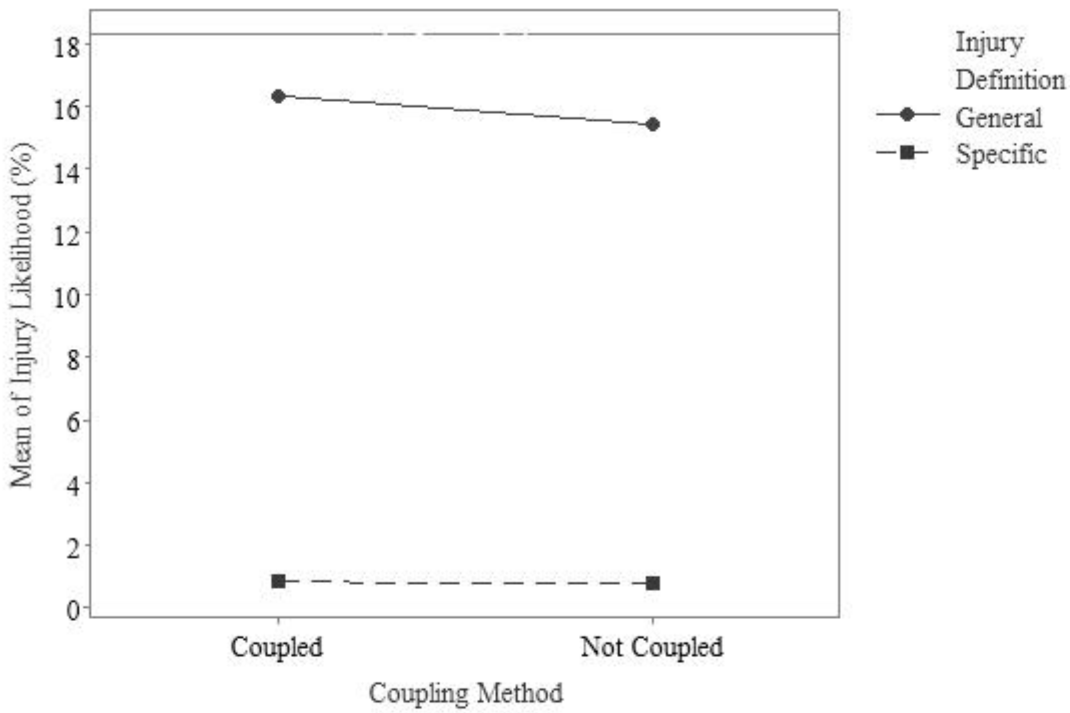

Figure 6. Two-factor factorial plot for the interaction effect between coupling method and injury definition on mean injury likelihood.

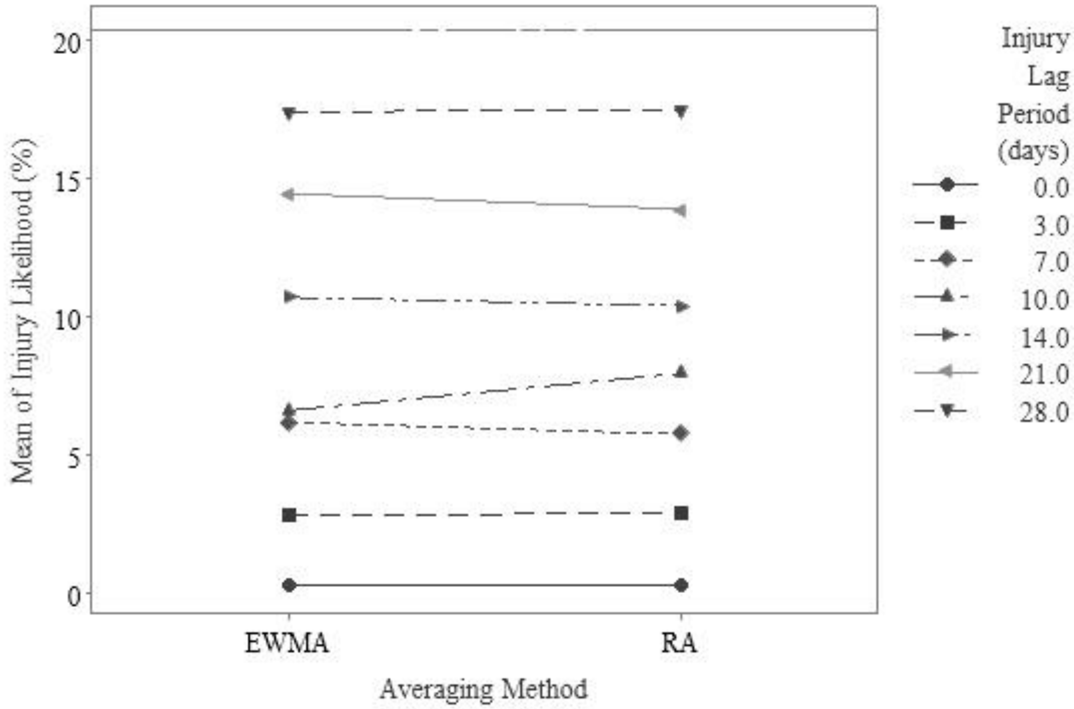

Figure 7. Two-factor factorial plot for the interaction effect between averaging method and injury lag period on mean injury likelihood.

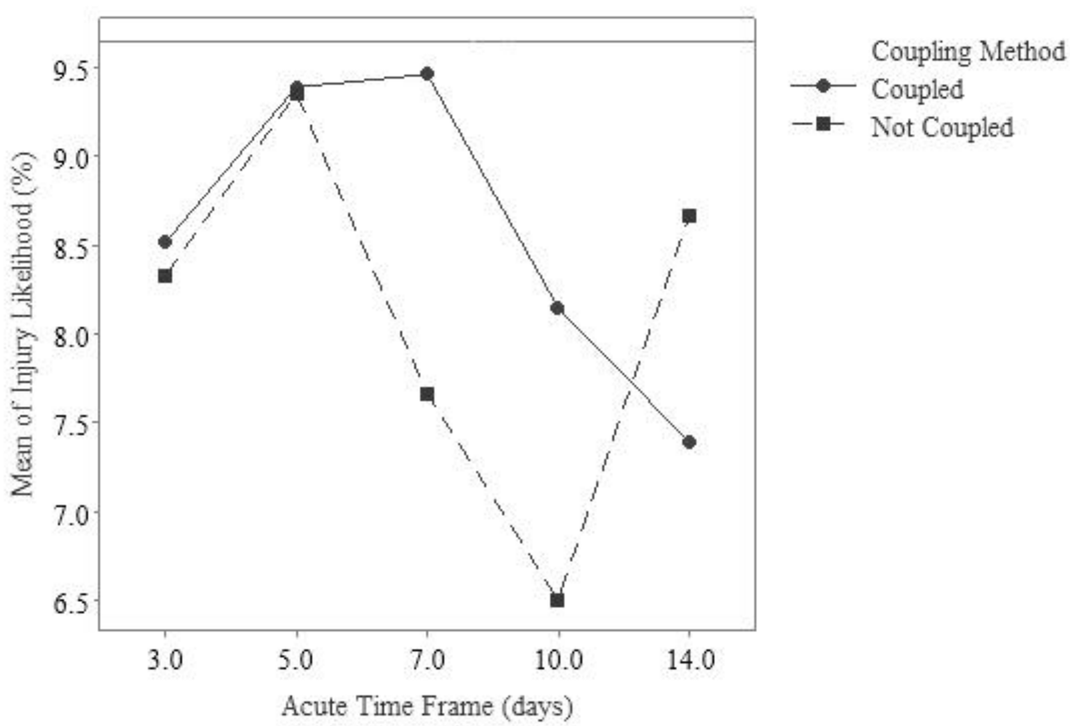

Figure 8. Two-factor factorial plot for the interaction effect between acute time frame and coupling method on mean injury likelihood.

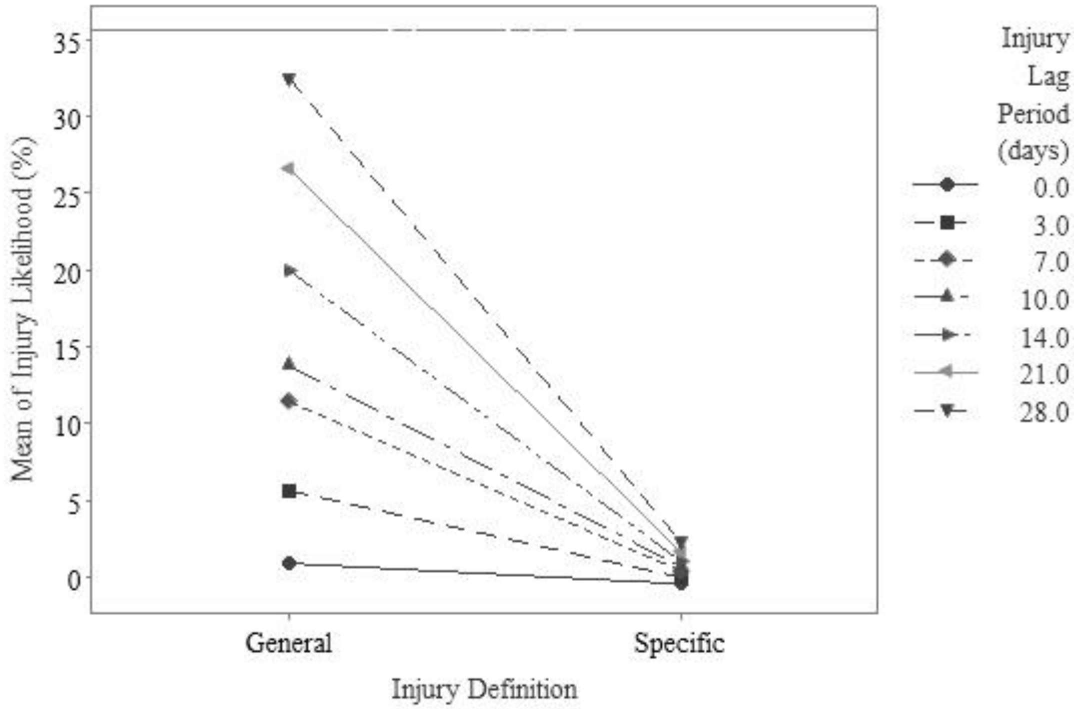

Figure 9. Two-factor factorial plot for the interaction effect between injury definition and injury lag period on mean injury likelihood.

Table 14. The dependency of factor levels within two-factor interactions for the interaction effect of given factors on mean injury likelihood. Factor dependencies were independent (I), dependent (D), insignificant (N), or unable to be determined by Minitab (X).

	Input	Averaging Method	Coupling Method	Acute Time Frame	Chronic Time Frame	Injury Definition	Injury Lag Period
Input	-	D	D	D	D	D	I
Averaging Method	D	-	D	D	D	N	I
Coupling Method	D	D	-	D	D	I	I
Acute Time Frame	D	D	D	-	X	I	I
Chronic Time Frame	D	D	D	X	-	I	I
Injury Definition	D	N	I	I	I	-	D
Injury Lag Period	I	I	I	I	I	D	-

Input and averaging method were each independent of the level within injury lag period and dependent on the level within all other factors; though, the interaction between averaging method and injury definition was not statistically significant. Coupling method, acute time frame, and chronic time frame were each independent of the level within injury definition and lag period and dependent on the level within all other factors; however, the factorial plot for the effect between acute and chronic time frame on injury likelihood was indeterminable by Minitab. Injury definition was dependent on the level within injury lag period and input and independent of the level with all other factors, except averaging method as previously mentioned. Injury lag period was dependent on the level within injury definition and independent of the level with all other factors.

Discussion

Main and Interaction Effects

The current literature demonstrates selecting the ACWR and injury methodologies required for conducting an injury likelihood analysis without considering how the methodologies interact with each other. Chapter 2 showed that when considering ACWR input and computation components in isolation, there were statistically significant differences between various levels that would likely not make any practical difference, but there were compounding effects that could have a practical significance when ACWR components interact. In this study, injury methodologies were added to those required for ACWR computations. Subsequently, the statistically significant differences within injury definition and injury lag period would likely have practical significance, while the differences within ACWR input and computation components would likely not. Therefore, when considering injury likelihood components in isolation, practitioners would need to make decisions regarding which injury definition and lag period to use, but any VBD input and ACWR model would be sufficient when the values between different configurations are interpreted with equivalent criteria. However, similar to ACWR computation, when considering the interactions between injury likelihood components, there are compounding effects between components that could have a practical significance. Consequently, practitioners should not select ACWR and injury methodologies for injury likelihood analyses in isolation and should develop their strategies by progressing through a component hierarchy that establishes the impact of each component based on their interactions with other components.

The methodological differences between studies in the literature may be contributing to the inconclusive implications associated with injury analyses using injury likelihood and ACWR because those studies do not consider the impact of all components interacting together. In addition to the effects between injury likelihood groups being caused by the methodologies used to compute their values, differing datasets may also produce different results. The analytical processes used in this study can be replicated by practitioners to guide the development of an injury likelihood analysis within the context of their own environment.

Component Hierarchy

The results of this study suggest the methodologies associated with injury likelihood using ACWR should be developed in a hierarchical order: 1) injury definition, 2) injury lag period, 3) input, 4) chronic time frame, 5) acute time frame, 6) averaging method, and 7) coupling method. Injury definition and lag period contributed to more injury likelihood variation than the other components, and the effect of each depended on the level of the other. However, injury definition caused greater differences in injury likelihood within its levels than injury lag period and influenced the effect of input. Input caused a smaller variation in injury likelihood than injury definition and lag period but a larger variation than all other components. Input also influenced the effect of acute time frame, chronic time frame, averaging method, and coupling method. Acute and chronic time frames had similar contributions to injury likelihood variation and larger contributions than averaging and coupling method. The time frames also had similar differences in injury likelihood within their levels, and the effect of both time frames depended on the level of the other. Averaging and coupling methods had similar contributions to injury likelihood variation, which was smaller than all other factors. The effect of both methods also depended on the level of the other. Generally, the components used within the injury criterion were more important than all other components, and input was more important than the components used within the ACWR model. However, the combined effect of all four computational components may be greater than input alone.

Injury Criterion Interactions

Though interactions between injury criterion and ACWR components were significant, the only dependency between them was injury definition and input, which may suggest a mechanistic relationship between them. However, as a definition expands in features and becomes more specific to a scenario, the number of injuries available for an analysis would either decrease or stay the same, which may statistically limit the feasibility of a mechanistically driven analysis. Considering the component hierarchy, processes for determining the most beneficial injury definition relative to a sport organization’s goals, objectives, and data should be developed, and inputs mechanistically or statistically suited to the definition should be included.

Within the injury criterion, the definition also had a dependency with the lag period. When a definition was satisfied within a lag period, all ACWRs up until the time of the injury were linked to that injury. Consequently, as definitions include more injuries and lag periods increase, more ACWRs will be associated with injuries; supporting injury analyses may be statistically driven to some degree. Further research is needed to investigate criteria used with injury lag periods, and any specific mechanisms driving the criteria should align with the injury definition.

Effects on Injury Likelihood vs ACWR

The input, averaging method, coupling method, acute time frame, and chronic time frame were common components between ACWR and injury likelihood, where their methodological effects on ACWR were investigated in Chapter 2. Each component had significant main and interaction effects on the respective response variables, and input was the only component where the levels were further reduced in the likelihood analysis. Input also had a greater impact on the variation of the response variable than the factors associated with the computational model. Variation in the response from each component was generally smaller in the likelihood analysis, though most variations had small magnitudes in both analyses and the corresponding effects compounded as different components interacted. Furthermore, averaging method within the ACWR analysis was the only instance where a component was independent of levels within other components, but it was dependent on all ACWR components within the likelihood analysis. The differences between the studies may be influenced by reducing the dataset between studies and between main and interaction analyses within each study to accommodate hardware limitations.

Binning and Interpolation

Previous studies have binned ACWR’s into discrete categories using standard deviations, z-scores, percentiles, constant increments, arbitrary bins, and others where studies using similar methods also had a varying number of categories (Andrade et al. 2020). These methods demonstrate fitting data to arbitrary models where injury likelihood is modelled as a series of constant piecewise functions, and their use has been shown to cause a higher risk of type-I and type-II error (Carey et al. 2018). Continuous methods better model the nonlinear relationship between ACWR and injury likelihood than discrete models, and restricted cubic splines are continuous models that can fit local features within data better than fractional polynomials (Carey et al. 2018). However, cubic splines still require a method for determining knots used to construct the model. The binning optimization algorithm used in this study objectively created knots for the cubic spline function within each group by generating the number of bins and width of each bin while considering the binary characteristic of the injury criterion. The combination of binning optimization and cubic spline interpolation fit the injury likelihood profile to the data specific to each group, but the process may benefit from alternative criterions or additional constraints.

Limitations

As mentioned in Chapter 2, the statistical differences between inputs may be influenced by the use of absolute velocity bands, the ranges associated with those velocity bands, and only considering velocity to discriminate between distances. The dependencies and thus the hierarchy of injury likelihood components were also affected by the subjective interpretation of the two-factor factorial plots.

The data associated with the ACWR methods included in this study were based on the reduced methods from the ACWR analysis in Chapter 2. The effects were assumed to be constant for injury likelihood due to the memory required to include data generated for all configurations in the statistical analysis exceeding the available memory of a desktop computer. Additionally, the recording of injuries by an athletic trainer was subjected to inter- and intra-rater reliability from three athletic trainers over the time period of this study. Injury recordings may have also been impacted by the timing in which an injury was reported by a subject. Furthermore, this study only investigated effects based on the injury likelihood magnitudes. Due to injury likelihood being determined from a profile, various configurations may exhibit similar magnitudes but different patterns between profiles that may further impact the development of injury likelihood methodologies.

Conclusions

Interactions between injury likelihood methodologies using ACWR contribute to the inconclusive implications associated with ACWR in the literature. When considering injury likelihood using ACWR, methodologies associated with a given component should not be determined without considering its interactions with other components. Practitioners should reduce methodologies from the literature and establish a hierarchy that guides the development of their IMS based on the needs of their specific environment. Alternately, the determination of injury definition and lag period should be prioritized over the input, and input should be prioritized over the components within the

ACWR model. Then, the ACWR model should be developed by selecting the methods for chronic time frame, acute time frame, averaging method, and then coupling method. At some point within the development progression, the specific level selected within a component may not provide a practical benefit over other options.

CHAPTER 4

EFFECTS OF ACUTE:CHRONIC WORKLOAD RATIO METHODOLOGIES ON THE PEAK ACCURACY OF AN INJURY MITIGATION STRATEGY IN WOMEN'S COLLEGIATE FIELD HOCKEY

Background and Significance

Strategies for using acute:chronic workload ratios (ACWRs) to mitigate sport-related injuries have primarily been driven by associating ACWRs with levels of injury risk (Griffin et al. 2020; Andrade et al. 2020). However, the literature has criticized the practical significance of this approach. A study reported increased injury risks at higher ACWRs even though the absolute risk was only approximately 4% and the difference in risk between moderate and high ACWRs was approximately 3% (N. B. Murray et al. 2016). Furthermore, studies have reported ACWR models have poor or no predictive ability due to results with higher incidences of false-positive predictions than true-positive (Fanchini et al. 2018; McCall, Dupont, and Ekstrand 2018). The results of Chapters 2 and 3 showed methodological decisions can significantly impact ACWR and injury likelihood, and the practical implementation of an ACWR strategy may be based on the specific methodologies used. Consequently, when developing and evaluating an injury mitigation strategy (IMS) using ACWR, the performance of the strategy should be considered.

No studies were identified that have developed an IMS by optimizing outcomes within a contingency table or investigating the effects of methodological decisions on the performance of a strategy, such as sensitivity, specificity, or accuracy. Sensitivity refers to the probability of an IMS identifying an athlete being injured given an athlete was injured, and specificity refers to the probability of an IMS identifying an athlete not being injured given an athlete was not injured. A strategy with high sensitivity would identify more injury incidences than a strategy with low sensitivity. However, a strategy with high sensitivity may also have low specificity, which could negatively impact the practical implementation of the strategy. Delecroix et al. noted the criteria they used with ACWR did not have high sensitivity or specificity (Delecroix et al. 2018), while Fanchini et al. reported sensitivities from 12.5-43.1% and specificities from 65.3-85.3% between six different ACWR configurations (Fanchini et al. 2018). In order to balance sensitivity and specificity, the accuracy of an IMS can be maximized by varying the ACWR criteria used within it; thus, maximizing the probability of identifying a true event.

Specific Aims

The purpose of this study was to investigate the main and interaction effects of injury definition, injury lag period, input, averaging method, coupling method, acute time frame, and chronic time frame on the peak accuracy of an ACWR-based IMS. Because mitigating injuries is the priority, the results inform the development of an IMS by identifying methodologies with significant effects on accuracy.

The specific aims of this chapter were:

1. Determine if input (i.e., velocity-based distances) had a main effect or interaction effect with averaging method, coupling method, acute time frame, chronic time frame, injury definition, and/or injury lag period on the peak accuracy of an IMS.
    - *Hypothesis: The null hypothesis was input did not have a main effect on peak accuracy, and the alternate hypothesis was input had a main effect.*
    - *Hypothesis: The null hypothesis was input did not have an interaction effect on peak accuracy, and the alternate hypothesis was input had an interaction effect.*
    - *Key Question: If a null hypothesis was rejected, which input levels had a not different effect on peak accuracy?*
    - *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different input levels on peak accuracy?*
2. Determine if averaging method (i.e., rolling and exponentially weighted moving average) had a main effect or interaction effect with input, coupling method, acute time frame, chronic time frame, injury definition, and/or injury lag period on the peak accuracy of an IMS.
    - *Hypothesis: The null hypothesis was averaging method did not have a main effect on peak accuracy, and the alternate hypothesis was averaging method had a main effect.*
    - *Hypothesis: The null hypothesis was averaging method did not have an interaction effect on peak accuracy, and the alternate hypothesis was averaging method had an interaction effect.*

- *Key Question: If a null hypothesis was rejected, which levels within averaging method had a not different effect on peak accuracy?*
- *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different averaging method levels on peak accuracy?*

3. Determine if coupling method (i.e., coupled and not coupled) had a main effect or interaction effect with input, averaging method, acute time frame, chronic time frame, injury definition, and/or injury lag period on the peak accuracy of an IMS.
    - *Hypothesis: The null hypothesis was coupling method did not have a main effect on peak accuracy, and the alternate hypothesis was coupling method had a main effect.*
    - *Hypothesis: The null hypothesis was coupling method did not have an interaction effect on peak accuracy, and the alternate hypothesis was coupling method had an interaction effect.*
    - *Key Question: If a null hypothesis was rejected, which levels within coupling method had a not different effect on peak accuracy?*
    - *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different coupling method levels on peak accuracy?*
4. Determine if acute time frame (i.e., 3-14 days) had a main effect or interaction effect with input, averaging method, coupling method, chronic time frame, injury definition, and/or injury lag period on the peak accuracy of an IMS.

- *Hypothesis: The null hypothesis was acute time frame did not have a main effect on peak accuracy, and the alternate hypothesis was acute time frame had a main effect.*
- *Hypothesis: The null hypothesis was acute time frame did not have an interaction effect on peak accuracy, and the alternate hypothesis was acute time frame had an interaction effect.*
- *Key Question: If a null hypothesis was rejected, which levels within acute time frame had a not different effect on peak accuracy?*
- *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different acute time frame levels on peak accuracy?*

5. Determine if chronic time frame (i.e., 3-7 weeks) had a main effect or interaction effect with input, averaging method, coupling method, acute time frame, injury definition, and/or injury lag period on the peak accuracy of an IMS.
    - *Hypothesis: The null hypothesis was chronic time frame did not have a main effect on peak accuracy, and the alternate hypothesis was chronic time frame had a main effect.*
    - *Hypothesis: The null hypothesis was chronic time frame did not have an interaction effect on peak accuracy, and the alternate hypothesis was chronic time frame had an interaction effect.*
    - *Key Question: If a null hypothesis was rejected, which levels within chronic time frame had a not different effect on peak accuracy?*

- *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different chronic time frame levels on peak accuracy?*

6. Determine if injury definition (i.e., general and specific) had a main effect or interaction effect with input, averaging method, coupling method, acute time frame, chronic time frame, and/or injury lag period on the peak accuracy of an IMS.
    - *Hypothesis: The null hypothesis was injury definition did not have a main effect on peak accuracy, and the alternate hypothesis was injury definition had a main effect.*
    - *Hypothesis: The null hypothesis was injury definition did not have an interaction effect on peak accuracy, and the alternate hypothesis was injury definition had an interaction effect.*
    - *Key Question: If a null hypothesis was rejected, which injury definition levels had a not different effect on peak accuracy?*
    - *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different injury definition levels on peak accuracy?*
7. Determine if injury lag period (i.e., 0-28 days) had a main effect or interaction effect with input, averaging method, coupling method, acute time frame, chronic time frame, and/or injury definition on the peak accuracy of an IMS.

- *Hypothesis: The null hypothesis was injury lag period did not have a main effect on peak accuracy, and the alternate hypothesis was injury lag period had a main effect.*
- *Hypothesis: The null hypothesis was injury lag period did not have an interaction effect on peak accuracy, and the alternate hypothesis was injury lag period had an interaction effect.*
- *Key Question: If a null hypothesis was rejected, which injury lag period levels had a not different effect on peak accuracy?*
- *Key Question: If a null hypothesis was rejected and the levels were different, what was the effect of the different injury lag period levels on peak accuracy?*

8. Compare the effects of input, averaging method, coupling method, acute time frame, and chronic time frame factors and their respective factor levels between ACWR and the peak accuracy of an IMS.
    - *Key Question: Were the input factor and factor level effects consistent between ACWR and peak accuracy analyses?*
    - *Key Question: Were the averaging method factor and factor level effects consistent between ACWR and peak accuracy analyses?*
    - *Key Question: Were the coupling method factor and factor level effects consistent between ACWR and peak accuracy analyses?*
    - *Key Question: Were the acute time frame factor and factor level effects consistent between ACWR and peak accuracy analyses?*

- *Key Question: Were the chronic time frame factor and factor level effects consistent between ACWR and peak accuracy analyses?*

9. Compare the effects of input, averaging method, coupling method, acute time frame, chronic time frame, injury definition, and injury lag period factors and their respective factor levels between injury likelihood and the peak accuracy of an IMS.

    - *Key Question: Were the input factor and factor level effects consistent between injury likelihood and peak accuracy analyses?*
    - *Key Question: Were the averaging method factor and factor level effects consistent between injury likelihood and peak accuracy analyses?*
    - *Key Question: Were the coupling method factor and factor level effects consistent between injury likelihood and peak accuracy analyses?*
    - *Key Question: Were the acute time frame factor and factor level effects consistent between injury likelihood and peak accuracy analyses?*
    - *Key Question: Were the chronic time frame factor and factor level effects consistent between injury likelihood and peak accuracy analyses?*
    - *Key Question: Were the injury definition factor and factor level effects consistent between injury likelihood and peak accuracy analyses?*
    - *Key Question: Were the injury lag period factor and factor level effects consistent between injury likelihood and peak accuracy analyses?*

Methodology

This study was approved by the University of Louisville Internal Review Board. Written informed consent was obtained from each participant, when possible. Written informed consent was waived by the review board when its acquisition was not practically obtainable (i.e. subjects were no longer affiliated with the respective organization).

Subjects

Female student-athletes on the University of Louisville field hockey team during the 2017-18 to 2022-23 pre-seasons, in-seasons, and post-seasons were invited to participate as subjects. There were 55 subjects included in this study.

Data Collection

ACWRs computed in Chapter 2 that had factors and factor levels with statistically significant and different effects on ACWR were used. Configurations with significant and different effects included velocity-based distances (VBDs) from velocity bands 3-6, band 5, bands 5-8, band 6, bands 6-8, bands 7-8, and band 8; rolling average (RA) and exponentially weighted moving average (EWMA) averaging methods; coupled and not coupled coupling methods; acute time frames of 3, 5, 7, 10, and 14 days; and chronic time frames of 21, 28, 35, 42, and 49 days. Each ACWR was expressed as a value between 0 and 100% of the respective group range, and outliers within each group were removed using the interquartile range method.

Injury criterions established in Chapter 3 were also used. The injury criterion determined if an ACWR was associated with an injury based on an injury definition and injury lag period. If the injury definition was satisfied within the injury lag period following an ACWR exposure, the ACWR was associated with an injury. If the injury definition was not satisfied within the injury lag period following an ACWR exposure, the ACWR was not associated with an injury. Injury data collected during the 2018-19 to 2022-23 pre-seasons, in-seasons, and post-seasons was included; though, data from the 2020-21 season was excluded due to events associated with COVID-19. There were 158 injury instances included. Two injury definitions were used based on practical outcomes: 1) the athletic trainer recorded a subject was exposed to a sport-related muscle, tendon, ligament, or bone injury in the lower body or torso; 2) the athletic trainer recorded a subject was exposed to a sport-related muscle, tendon, ligament, or bone injury in the lower body or torso, and the subject missed a training or competition session. Injury lag period consisted of time frames of 0, 3, 7, 10, 14, 21, and 28 days following an ACWR exposure.

Data Processing

The peak accuracy of an injury mitigation strategy was determined for each configuration of input, averaging method, coupling method, acute time frame, chronic time frame, injury definition, and injury lag period factor levels. Accuracy was calculated using

$$A = \frac{T_P + T_N}{T_P + F_P + F_N + T_N} \tag{7}$$

where T_P, T_N, F_P, and F_N were the number of true positive, true negative, false positive, and false negative events, respectively. The number of true positive, true negative, false positive, and false negative events was determined using an injury criterion and ACWR-based risk acceptance threshold. A true positive event occurred when ACWR was above the acceptance threshold and the injury criterion was satisfied. A false positive event occurred when ACWR was above the acceptance threshold and the injury criterion was not satisfied. A false negative event occurred when ACWR was below the acceptance threshold and the injury criterion was satisfied. A true negative event occurred when ACWR was below the acceptance threshold and the injury criterion was not satisfied. The injury criterion was satisfied when an injury definition was met within an injury lag period. The injury risk acceptance threshold was varied and used to iteratively maximize the accuracy of the configuration. Within the first iteration, accuracy was computed at 11 thresholds stepping from 0% to 100% of the respective ACWR distribution. The threshold steps directly below and above the maximum accuracy of the current iteration set the boundary conditions for the next iteration, which used 21 threshold steps. If there was not a threshold step above the maximum accuracy, the threshold steps directly below and at the maximum accuracy set the boundary conditions for the next iteration, which used 11 threshold steps. Seven iterations were used to determine the peak accuracy of the respective IMS, and the iteration steps progressed from 10% to 0.00001% with a 10% step reduction each iteration.

Statistical Analysis

The use of a desktop computer, rather than a supercomputing mainframe, necessitated the statistical analysis to be conducted in a two-stage approach using Minitab 12.4.1 (Minitab, LLC, State College, Pennsylvania). For the first stage, a general linear mixed model (GLMM) ANOVA was used to identify main effects of each factor (i.e., input, averaging method, coupling method, acute time frame, chronic time frame, injury definition, and injury lag period) on peak accuracy of an IMS. Input had seven VBD levels consisting of distances from velocity bands 3-6, band 5, bands 5-8, band 6, bands

6-8, bands 7-8, and band 8. Averaging method had two levels of RA and EWMA. Coupling method had two levels of coupled and not coupled. Acute time frame had five levels of 3, 5, 7, 10, and 14 days. Chronic time frame had five levels of 21, 28, 35, 42, and 49 days. Injury definition had two factor levels of general and specific definitions. Injury lag period had seven factor levels of 0, 3, 7, 10, 14, 21, and 28 days. Peak accuracy of an IMS was the response variable, and only main effects were included in the model. Factors with a p-value less than 0.05 were considered to be statistically significant and included in the Tukey test, which was used to identify levels within each factor that were not statistically different. After the Tukey test was performed, levels within each factor that were statistically not different from other levels were removed from the dataset for the second GLMM ANOVA. For the second stage, a GLMM ANOVA was used to determine the interaction effects between factors on peak accuracy of an IMS. All interactions between factors with a statistically significant main effect were included in the model. Interaction effects with a p-value less than 0.05 were considered to be statistically significant. Factorial plots were then generated for significant two-factor interactions to assess whether their impact on peak accuracy depended on the level of one of the factors.

Results

Main Effects and Tukey Test

Input, averaging method, coupling method, acute time frame, chronic time frame, injury definition, and injury lag period each had a statistically significant main effect on peak accuracy (p-values < 0.001). Therefore, the null hypothesis associated with the main effect of each factor was rejected, and the alternate hypothesis was accepted. All seven factors were included in the subsequent Tukey test. The Tukey test results for input, averaging method, coupling method, acute time frame, and chronic time frame following the main effects analysis are shown in Tables 15-21.

Table 15. Tukey test results for input in association with peak accuracy.

Input	n	Mean	Grouping	
VBD band 6	1344	92.179	A	
VBD bands 6-8	1344	92.160	A	
VBD bands 3-6	1344	92.152	A	
VBD bands 5-8	1344	92.119	A	
VBD band 5	1344	92.102	A	
VBD bands 7-8	1344	92.090	A	
VBD band 8	1344	90.715		B

Means that do not share a letter were significantly different.

Table 16. Tukey test results for averaging method in association with peak accuracy.

Averaging Method	n	Mean (%)	Grouping	
EWMA	4704	92.130	A	
RA	4704	91.732		B

Means that do not share a letter were significantly different.

Table 17. Tukey test results for coupling method in association with peak accuracy.

Coupling Method	n	Mean (%)	Grouping	
Not coupled	4704	92.128	A	
Coupled	4704	91.734		B

Means that do not share a letter were significantly different.

Table 18. Tukey test results for acute time frame in association with peak accuracy.

Acute Time Frame (days)	n	Mean (%)	Grouping		
3	1960	92.308	A		
5	1960	92.084	A	B	
7	1960	91.938		B	
10	1960	91.787		B	C
14	1568	91.539			C

Means that do not share a letter were significantly different.

Table 19. Tukey test results for chronic time frame in association with peak accuracy.

Chronic Time Frame (days)	n	Mean (%)	Grouping		
42	1960	92.357	A		
49	1960	92.248	A		
35	1960	92.124	A		
28	1960	91.746		B	
21	1568	91.181			C

Means that do not share a letter were significantly different.

Table 20. Tukey test results for injury definition in association with peak accuracy.

Definition	n	Mean (%)	Grouping	
Specific	4704	98.273	A	
General	4704	85.589		B

Means that do not share a letter were significantly different.

Table 21. Tukey test results for injury lag period in association with peak accuracy.

Lag Period (days)	n	Mean (%)	Grouping						
0	1344	98.731	A						
3	1344	96.429		B					
7	1344	93.657			C				
10	1344	92.036				D			
14	1344	90.029					E		
21	1344	87.260						F	
28	1344	85.376							G

Means that do not share a letter were significantly different.

Two of the seven inputs were statistically different, and the levels were reduced to the VBDs from bands 5-8 and band 8. Two of the five acute time frames were statistically different, and the levels were reduced to 3 and 10 days. Three of the five chronic time frames were statistically different, and the levels were reduced to 21, 28, and 35 days. All the levels within averaging method, coupling method, injury definition, and injury lag period were statistically different; and none of the levels within those factors were removed for the interaction effects analysis.

The effect of changes in VBDs on peak accuracy was inconclusive. Greater peak accuracies occurred when using the EWMA method compared to RA, not coupled workloads compared to coupled, and the specific definition compared to the general definition. There was a decreasing effect on peak accuracy as the duration of the acute time frame and injury lag period increased. There was an increasing effect on peak accuracy as the duration of the chronic time frame increased.

Interaction Effects and Factorial Plots

Input, averaging method, coupling method, acute time frame, chronic time frame, injury definition, and injury lag period each had a statistically significant 2-, 3-, 4-, 5-, and 6-factor interaction effect on peak accuracy (p-value < 0.001). Therefore, the null hypothesis associated with the interaction effect of each factor was rejected, and the alternate hypothesis was accepted.

The factorial plots in Figures 10 and 11 show interactions where the effect of one factor was determined to be independent of the level within another factor, while the factorial plots in Figures 12 and 13 show interactions where the effect of one factor was determined to be dependent of the level within another factor. The dependencies between interacting factors are shown in Table 22.

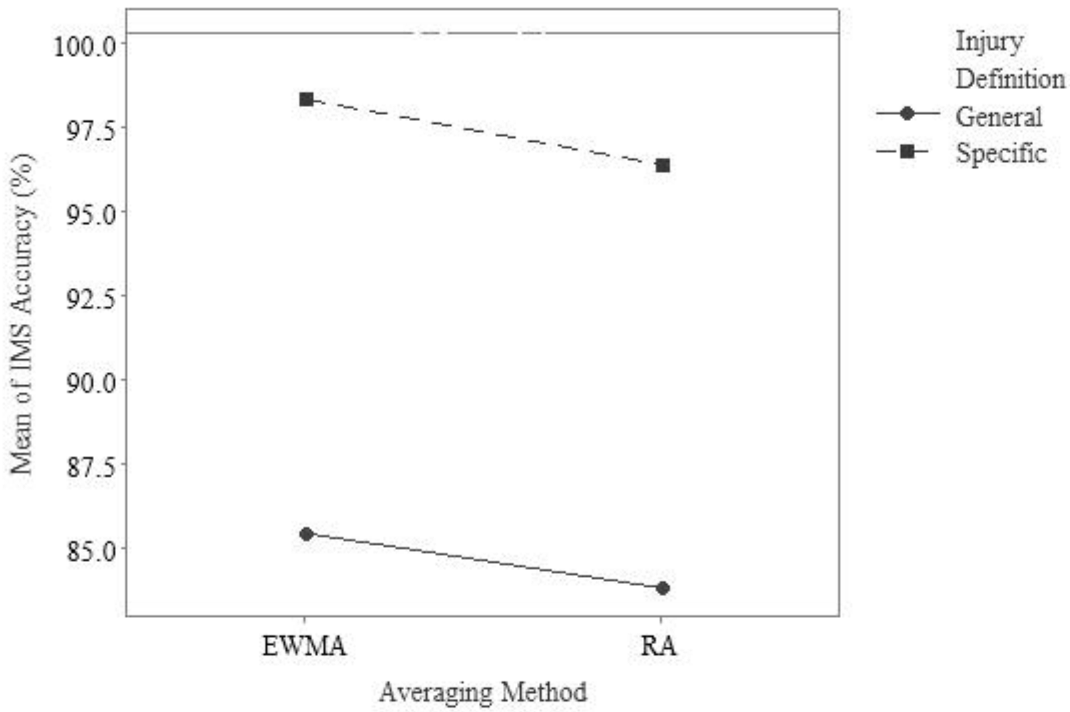

Figure 10. Two-factor factorial plot for the interaction effect between averaging method and injury definition on mean peak accuracy.

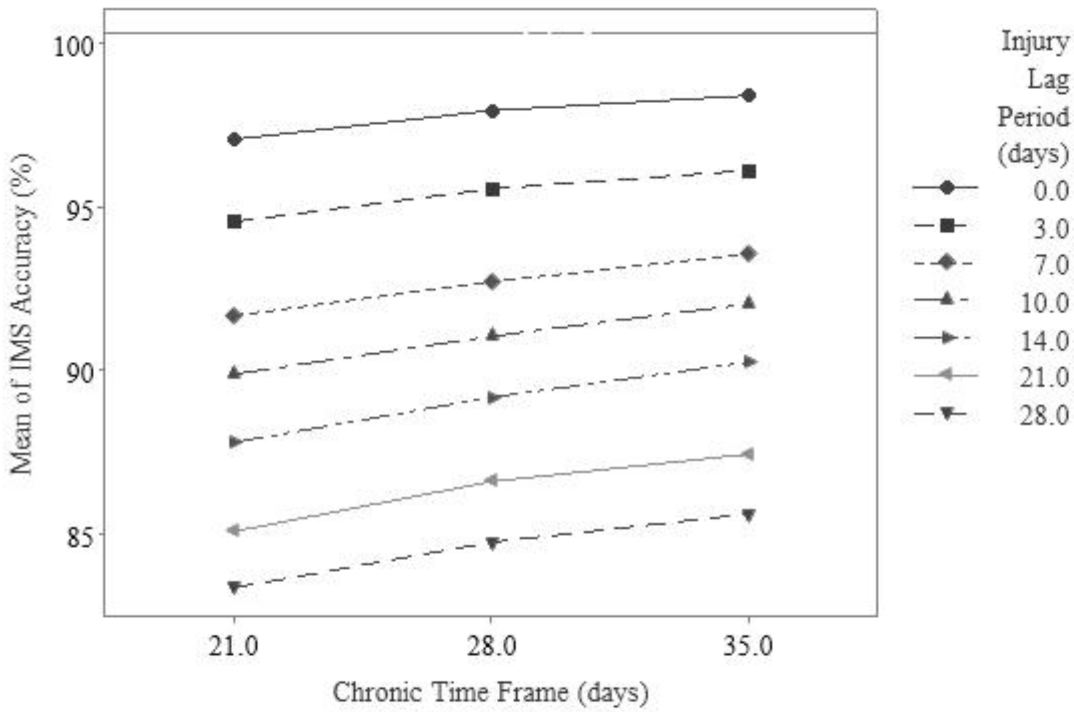

Figure 11. Two-factor factorial plot for the interaction effect between chronic time frame and injury lag period on mean peak accuracy.

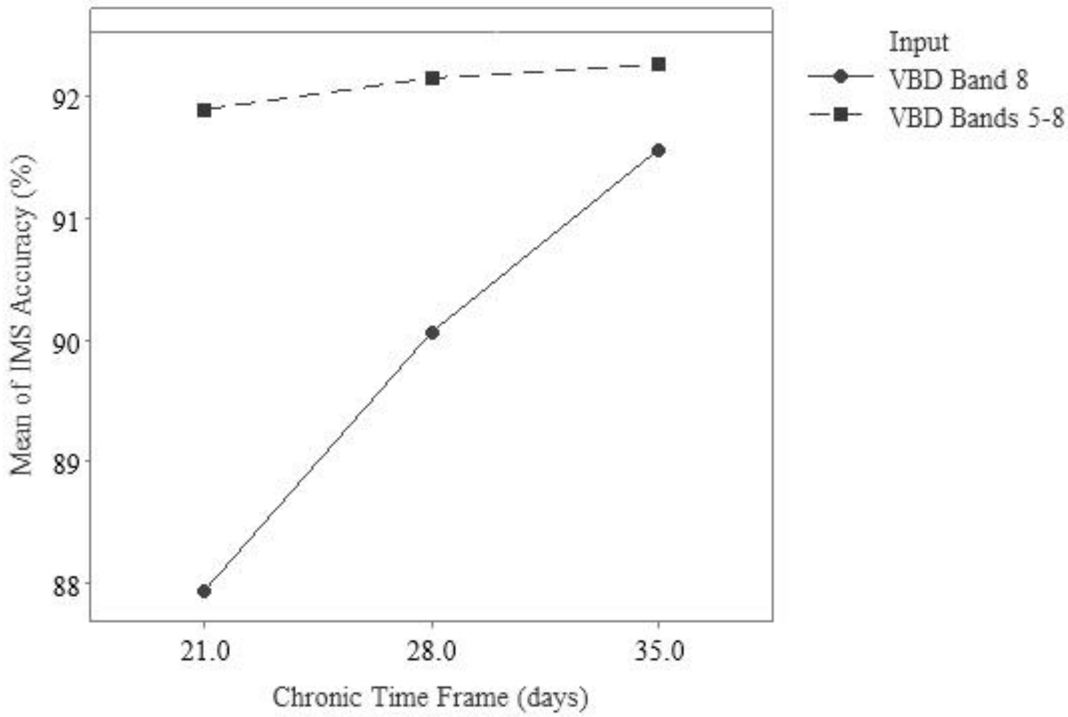

Figure 12. Two-factor factorial plot for the interaction effect between chronic time frame and input on mean peak accuracy.

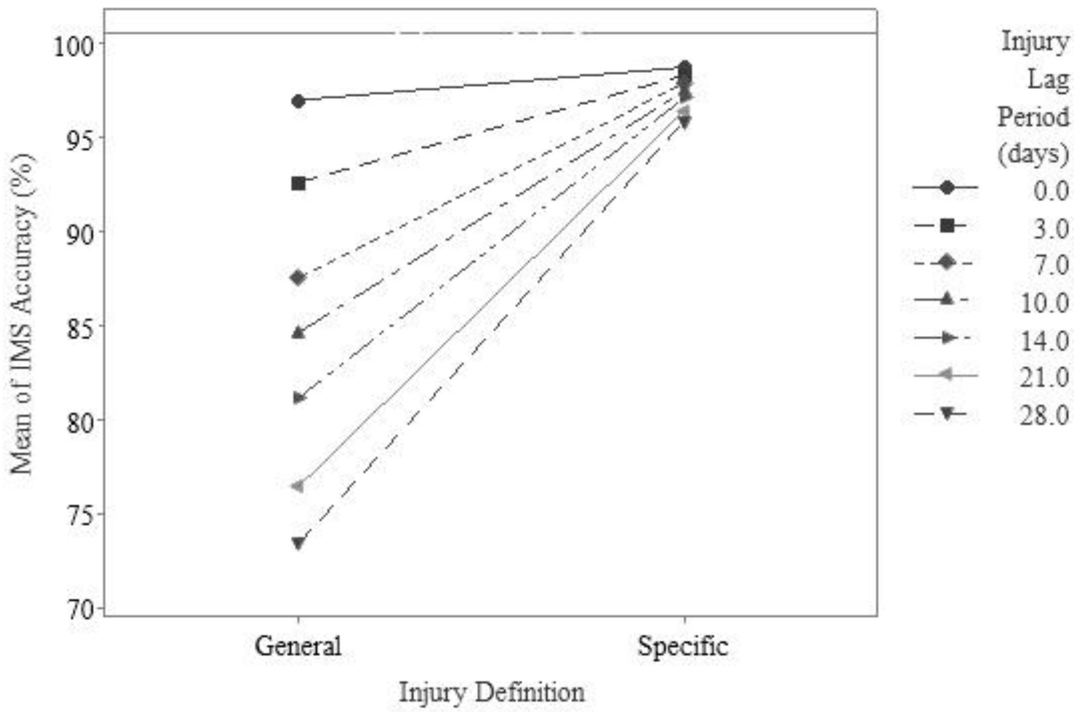

Figure 13. Two-factor factorial plot for the interaction effect between injury definition and injury lag period on mean peak accuracy.

Table 22. The dependency of factor levels within two-factor interactions for the interaction effect of given factors on mean peak accuracy. Factor dependencies were independent (I), dependent (D), insignificant (N), or unable to be determined by Minitab (X).

	Input	Averaging Method	Coupling Method	Acute Time Frame	Chronic Time Frame	Injury Definition	Injury Lag Period
Input	-	D	D	D	D	I	I
Averaging Method	D	-	D	D	D	I	I
Coupling Method	D	D	-	D	D	I	I
Acute Time Frame	D	D	D	-	D	I	N
Chronic Time Frame	D	D	D	D	-	I	I
Injury Definition	I	I	I	I	I	-	D
Injury Lag Period	I	I	I	N	I	D	-

Input, averaging method, coupling method, acute time frame, and chronic time frame were each independent of the level within injury definition and lag period and dependent on the level within all other factors; though, the interaction between acute time frame and injury lag period was not statistically significant. Injury definition was dependent on the level within injury lag period and independent of the level within all other factors. Injury lag period was dependent on the level within injury definition and independent of the level within all other factors, except acute time frame as previously mentioned.

Discussion

Main and Interaction Effects

Chapters 2 and 3 investigated methodological effects on ACWR's computation and application to injury likelihood, respectively. Both applications showed that when establishing each component within injury and ACWR methodologies in isolation, there were statistically significant differences between the respective levels that would likely not make any practical difference, but there were compounding effects that could have a practical significance when components interacted with each other. This study evaluated injury and ACWR methodologies within an accuracy-based application with similar results. When selecting methodologies in isolation, the statistically significant differences within injury definition and injury lag period would likely have practical significance, while the differences within ACWR input and computation components would likely not. Therefore, when considering components for the peak accuracy of an IMS in isolation, practitioners would need to make decisions regarding which injury definition and lag period to use, but any VBD input and ACWR model would be sufficient when the

ACWR values between different configurations are interpreted with equivalent criteria. However, similar to ACWR computation and injury likelihood, when considering the interactions between peak accuracy components, there are compounding effects between components that could have a practical significance. Consequently, practitioners should not select ACWR and injury methodologies for a peak accuracy analysis in isolation and should develop their strategies by progressing through a component hierarchy that establishes the impact of each component based on their interactions with other components.

Component Hierarchy

The results of this study suggest the methodologies associated with peak accuracy of an IMS using ACWR should be developed in a hierarchical order: 1) injury definition, 2) injury lag period, 3) input, 4) chronic time frame, 5) acute time frame, and 6) averaging and coupling method. Injury definition and lag period contributed to more variation in peak accuracy than other components, and the effect of both components depended on the level of the other. However, injury definition had greater differences in peak accuracy between its levels than injury lag period. Input caused less variation in peak accuracy than injury definition and lag period, while it caused more variation than all other components, and the effects of input influenced all ACWR model components. Acute and chronic time frames had similar differences in peak accuracy between their levels, but chronic time frame caused larger variation in peak accuracy than acute time frame. Averaging and coupling method caused the smallest variation in peak accuracy and had similar differences between their levels. Similar to hierarchies for the determination of ACWR and injury likelihood in Chapters 2 and 3, the methods used to establish an injury criterion were more important than all other components and input was more important than the components within the ACWR model. However, the combined effect of all four computation factors may be greater than input alone.

Performance-based Strategy Criterions

In addition to the interactions within the injury criterion and the ACWR computation, the strategy required a criterion for how ACWR was used with each configuration to identify true positive, true negative, false positive, and false negative outcomes. This study focused on peak accuracy performance where outcomes were influenced by an ACWR value being above a threshold. However, the ACWR criteria for a specific configuration likely depends on the methodology and data used. The ACWR literature currently associates injury likelihood with a U- or J-shaped profile (Andrade et al. 2020; Griffin et al. 2020), and the region within that profile where an organization's data falls could dictate whether an ACWR criteria should be above or below a threshold, within a range, or governed by an alternate criteria. Statistical assessments may also inform how many ACWR instances should be required to satisfy the criteria prior to an event outcome being identified. Then, specific strategies can be optimized for accuracy or some other performance parameter, such as sensitivity or specificity, based on the needs of an organization and the practicality of forecasting training and competitions loads to satisfy the criteria.

The strategy implemented in this study produced peak accuracies that ranged from 59-99% and were associated with ACWR thresholds that ranged from 57-99% of the respective distribution. A potential concern would be whether or not training and competition loads could practically be programmed to maintain ACWR values with high accuracy due to the criteria that would need to be met. Forecasting algorithms could project training and competition loads that support the development needs of a team or individuals across different phases of a macrocycle while determining if the criteria established by an IMS could be practically met. If the criteria could not be met, the strategy could be tuned to create the highest submaximal accuracy possible. However, the hierarchy of components should be investigated with submaximal accuracies to assess the consistency of their effects.

Effects on Peak Accuracy vs ACWR

Input, averaging method, coupling method, acute time frame, and chronic time frame were common components between ACWR and peak accuracy, where their methodological effects on ACWR were investigated in Chapter 2. Each component had significant main and interaction effects on the response variables; and input, acute time frame, and chronic time frame levels were further reduced in the peak accuracy analysis. The influence of input, coupling method, and acute time frame on the variation of peak accuracy was smaller compared to their impact in the ACWR analysis, while the influence of averaging method and chronic time frame was larger. Furthermore, in both analyses, input had a greater hierarchy than the components associated with the computational model. Averaging method within the ACWR analysis was the only instance where a factor was independent of levels within other factors, but it had dependencies on all ACWR factors within the peak accuracy analysis. The dependencies of all other factors were consistent between both analyses. Consequently, both analyses support developing ACWR-based injury mitigation strategies by prioritizing the input of the strategy over the components within the ACWR model.

Effects on Peak Accuracy vs Injury Likelihood

Input, averaging method, coupling method, acute time frame, chronic time frame injury definition, and injury lag period were common components between injury likelihood and peak accuracy, where their methodological effects on injury likelihood were investigated in Chapter 3, and each component had significant main and interaction effects on the response variables. Between both analyses, input was the only component with levels that were further reduced following the ACWR analysis in Chapter 2, but the levels were reduced more for peak accuracy than injury likelihood. Acute and chronic time frames also had levels further reduced, but only for peak accuracy. The influence of input, definition, and lag period on the variation of peak accuracy was smaller compared to their impact in the injury likelihood analysis, while the influence of averaging method, coupling method, acute time frame, and chronic time frame was larger. The levels within input and injury definition depended on each other within the likelihood analysis, but they were independent within the peak accuracy analysis. The dependencies of all other factors were consistent between both analyses. Also, in both analyses, the components associated with the injury criterion had a greater hierarchy than input, and input had a greater hierarchy than the components associated with the computational model. Consequently, both analyses support developing ACWR-based injury mitigation strategies by prioritizing the components within the injury criterion over the input and prioritizing the input over the components within the ACWR model.

Limitations

As mentioned in Chapter 2, the statistical differences between inputs may be influenced by the use of absolute velocity bands, the ranges associated with those velocity bands, and only considering velocity to discriminate between distances. The dependencies and thus the hierarchy of IMS peak accuracy components were also affected by the subjective interpretation of the two-factor factorial plots.

As mentioned in Chapter 3, the data associated with the ACWR methods included in this study were based on the reduced methods from the ACWR analysis in Chapter 2. The effects were assumed to be constant for IMS peak accuracy. Additionally, the recording of injuries by an athletic trainer was subjected to inter- and intra-rater reliability from three athletic trainers over the time period of this study. Injury recordings may have also been impacted by the timing in which an injury was reported by a subject.

Conclusions

Interactions between peak accuracy methodologies using ACWR contribute to the inconclusive implications associated with ACWR in the literature. When considering the peak accuracy of an IMS using ACWR, methodologies associated with a given component should not be determined without considering its interactions with other components. Practitioners should reduce methodologies from the literature and establish a hierarchy that guides the development of their IMS based on the needs of their specific environment. Alternately, the determination of injury definition and lag period should be prioritized over the input, and input should be prioritized over the components within the ACWR model. Then, the ACWR model should be developed by selecting the methods for chronic time frame, acute time frame, and then averaging and coupling method. At some point within the development progression, the specific level selected within a component may not provide a practical benefit over other options.

CHAPTER 5

RETROSPECTIVE CASE STUDY INVESTIGATING A PERFORMANCE-BASED INJURY MITIGATION STRATEGY USING ACUTE:CHRONIC WORKLOAD RATIOS

Background and Significance

The literature presents many injury criterion, model inputs, and computational configurations used to investigate injury mitigation strategies with acute:chronic workload ratios (ACWRs) (Andrade et al. 2020; Griffin et al. 2020). It cautions the application of ACWRs for injury mitigation due to inconclusive recommendations regarding which methodologies yield ACWR values that better inform the development of injury mitigating strategies. The literature has shown significant associations between ACWR ranges and injuries (Andrade et al. 2020; Griffin et al. 2020); however, some studies have demonstrated those associations have high relative risk with low absolute risk and poor injury prediction capabilities (Hulin et al. 2013; Delecroix et al. 2018; Fanchini et al. 2018; McCall, Dupont, and Ekstrand 2018; N. B. Murray et al. 2016). Chapters 2-4 showed injury definition, injury lag period, input, averaging method, coupling method, acute time frame, and chronic time frame had significant interaction effects on the response variable across multiple applications and suggested methodologies should be determined in a hierarchical order. However, data processing procedures may also affect how an injury mitigation strategy (IMS) is developed due to differences in data between studies.

When developing an IMS using ACWR, Chapters 2-4 support progressing through a general framework and analytically converging on the best strategy for a given dataset. After the injury criterion, quantifiable load, and computational model are determined and the various factors and factor levels that are not statistically different are reduced, several potential configurations for an IMS may remain. Those configurations could be further evaluated by backtesting and optimizing the variable parameters within the strategies. Backtesting has been extensively researched in financial risk applications. The general premise of backtesting involves assessing the hypothetical historical performance of a suggested strategy or evaluating risk models using historically forecasted and realized metrics (Christoffersen 2008). When developing an IMS, it can be developed and backtested using previous injuries. Though the IMS may not have prevented previous injuries from occurring, the investigation can provide insight into how the strategy could contribute to future mitigation efforts, such as the occurrence of injuries relative to the timeline of a competitive season or the types of injuries that occur.

In conjunction with backtesting, sensitivity and specificity of an IMS may provide insight into if and how a strategy should be implemented by a sport organization. Sensitivity indicates how well an IMS identifies an athlete being injured given they were injured, while specificity indicates how well an IMS identifies an athlete not being injured given they were not injured. A strategy with high sensitivity would identify more injured incidences than a strategy with low sensitivity and may help determine whether to proactively plan training and competition workloads to satisfy a supported criterion. A strategy with high specificity would identify more non-injured incidences than a strategy with low specificity and may help determine whether to reactively monitor and initiate recovery interventions following training and competition. However, in addition to the injury definition and lag period, input, averaging and coupling method, and acute and chronic time frame; the sensitivity and specificity associated with a strategy is directly impacted by the methods used to evaluate ACWR and injury criteria.

Specific Aims

The purpose of this study was to evaluate the accuracy, sensitivity, and specificity of various IMS configurations; and investigate the performance and application of a selected IMS relative to changes in the ACWR threshold. Applications were considered within the context of flagged and missed injuries within the seasonal timeline and by injury type.

The specific aims of this chapter were:

1. Evaluate the accuracy, sensitivity, and specificity of injury mitigation strategies optimized for peak accuracy.
    - *Key Question: Which methodological configurations had high accuracy and sensitivity?*
    - *Key Question: If there were configurations with high accuracy and sensitivity, what was the specificity associated with those configurations?*
2. Discuss the occurrence of flagged and missed injuries relative to the timeline of each season.

- *Key Question: Were there any points within a season where more injuries were missed than flagged?*
- *Key Question: Were there any points within the timeline where a similar number of injuries were missed and flagged?*
- *Key Question: Were there any points within a season where fewer injuries were missed than flagged?*

3. Discuss the occurrence of flagged and missed injuries relative to injury type.
    - *Key Question: Due to the injury criterion used, were any missed injuries a concern?*
    - *Key Question: Which injury types had more missed occurrences than flagged?*

Methodology

This study was approved by the University of Louisville Internal Review Board. Written informed consent was obtained from each participant, when possible. Written informed consent was waived by the review board when its acquisition was not practically obtainable (i.e. subjects were no longer affiliated with the respective organization).

Subjects

Female student-athletes on the University of Louisville field hockey team during the 2017-18 to 2022-23 pre-seasons, in-seasons, and post-seasons were invited to participate as subjects. There were 55 subjects included in the study.

Data Collection

From Chapter 2, all computed ACWRs were included. The configurations consisted of 36 velocity-based distances (e.g., distance from velocity band 1, distance from velocity bands 2-5, distance from velocity bands 1-8, etc.); rolling average (RA) and exponentially weighted moving average (EWMA) averaging methods; coupled and not coupled coupling methods; acute time frames of 3, 5, 7, 10, and 14 days; and chronic time frames of 14, 21, 28, 35, 42, 49, and 56 days. Each ACWR was expressed as a value between 0 and 100% of the respective group range, and outliers within each group were removed using the interquartile range method. From Chapter 3, sport-related injury data was included. All injuries were recorded by the team athletic trainer during the 2018-19 to 2022-23 pre-seasons, in-seasons, and post-seasons; however, data from the 2020-21 season was excluded due to events associated with COVID-19. There were 158 injury instances included. The injury likelihood profile of the selected IMS configuration was also included.

Data Processing

Injury criterions determined if an ACWR was associated with an injury based on an injury definition and injury lag period. If the injury definition was satisfied within the injury lag period following an ACWR exposure, the ACWR was associated with an injury. If the injury definition was not satisfied within the injury lag period following an ACWR exposure, the ACWR was not associated with an injury. Two injury definitions were used based on practical outcomes: 1) the athletic trainer recorded a subject was exposed to a sport-related muscle, tendon, ligament, or bone injury in the lower body or torso; 2) the athletic trainer recorded a subject was exposed to a sport-related muscle, tendon, ligament, or bone injury in the lower body or torso, and the subject missed a training or competition session. Injury lag period consisted of time frames of 0, 3, 7, 10, 14, 21, and 28 days following an ACWR exposure.

The false negative, false positive, true negative, and true positive outcomes associated with the injury mitigation strategy for all configurations were used to determine the sensitivity and specificity of the strategy, where the outcomes were based on the ACWR threshold at peak accuracy. Peak accuracy was determined using the processes from Chapter 4. A true positive event occurred when ACWR was above the threshold and the injury criterion was satisfied. A false positive event occurred when ACWR was above the threshold and the injury criterion was not satisfied. A false negative event occurred when ACWR was below the threshold and the injury criterion was satisfied. A true negative event occurred when ACWR was below the threshold and the injury criterion was not satisfied. Sensitivity was calculated using

$$S = \frac{T_P}{T_P + F_N} \tag{8}$$

where T_P and F_N were the number of true positive and false negative events, respectively. The specificity of each configuration was calculated using

$$P = \frac{T_N}{T_N + F_P} \tag{9}$$

where T_N and F_P were the number of true negative and false positive events, respectively.

Configuration A was selected for the investigation of an individual strategy and consisted of the distance accumulated at velocities greater than 4 m/s, exponentially weighted moving averaging, coupled acute and chronic workloads, 7-day acute time frame, 28-day chronic time frame, general injury definition, and 10-day injury lag period.

Configuration A included common methodologies used in the literature (Andrade et al. 2020; Griffin et al. 2020). The performance of Configuration A was based on the accuracy, sensitivity, and specificity of the associated IMS, where the ACWR threshold was varied from 0-100% of the ACWR distribution at 5% intervals. The IMS accuracy at each threshold was calculated using Equation (7). Injuries were flagged by the IMS when at least one true positive event was within the injury lag period prior to each injury for thresholds of 25% (low), 50% (moderate), and 75% (high) of the ACWR distribution, and injuries were missed when there were no true positive events within the injury lag period. Injuries that occurred within the initialization phase of ACWR (i.e., the first 28 days of training) were excluded.

Performance of IMS Configurations

The specificity and sensitivity, accuracy and sensitivity, and accuracy and specificity of 64,512 injury mitigation strategy configurations optimized for peak accuracy are shown in Figures 14-16, respectively.

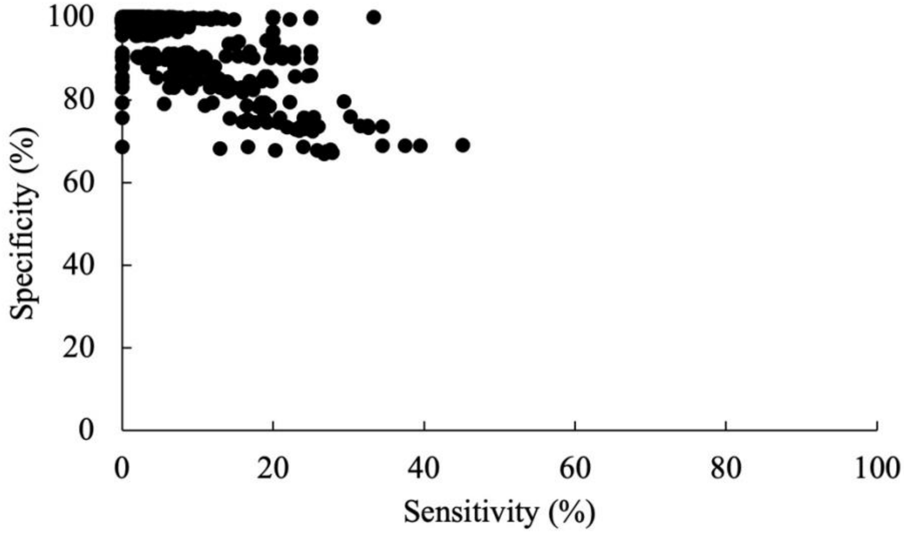

Figure 14. IMS specificity and sensitivity of 64,512 configurations optimized for peak accuracy.

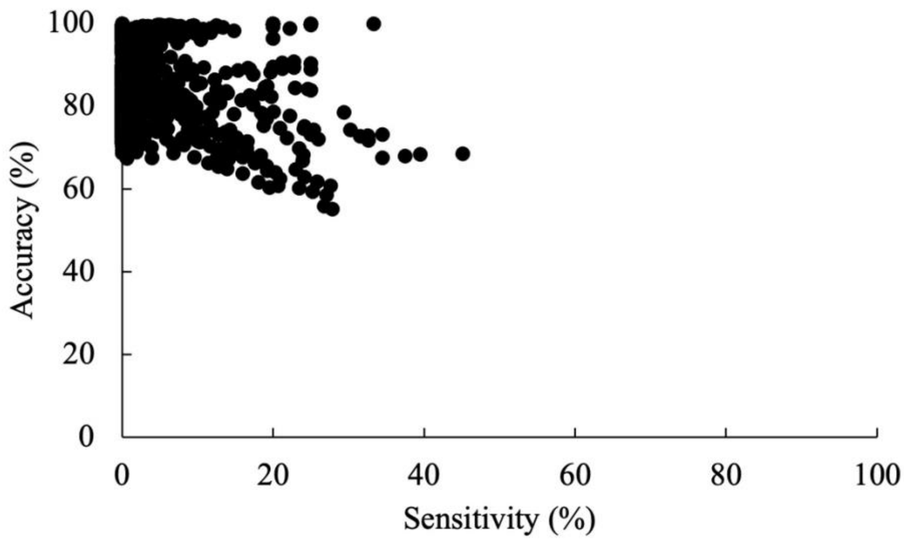

Figure 15. IMS accuracy and sensitivity of 64,512 configurations optimized for peak accuracy.

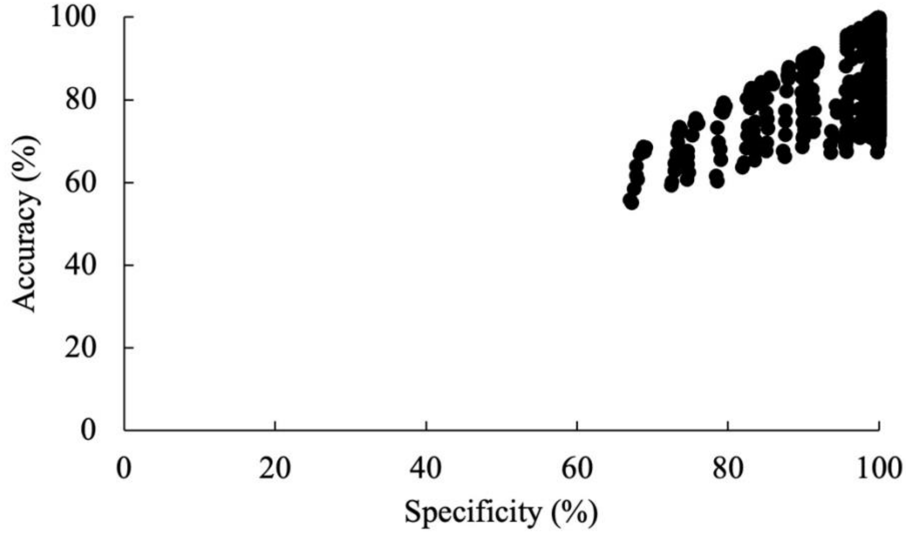

Figure 16. IMS accuracy and specificity of 64,512 configurations optimized for peak accuracy.

When using velocity-based distances within IMSs optimized for peak accuracy, the performance of the strategies generally exhibited high accuracy, low sensitivity, and high specificity. There was not an individual or group of configurations with high accuracy and high sensitivity, which may limit the current methodologies from being used to forecast training loads using ACWR criteria to mitigate injuries. However, due to the presence of configurations with high accuracy and high specificity, current methodologies could be used to reactively monitor and initiate recovery interventions.

The number of ACWR exposures may overpower the number of injuries resulting in instances where peak accuracy had few true positive instances. The number of exposures could be reduced by adapting the injury definition to consider additional components such as player position, development level, or role within the team. However, efforts to reduce the number of exposures may also reduce the number of injuries. Strategies may also benefit from optimizing accuracy within a submaximal range or an alternative ACWR threshold method, such as below a threshold or inside or outside of a band.

Investigation of Selected IMS Configuration

Figure 17 shows the accuracy, sensitivity, and specificity of Configuration A with a varied ACWR threshold.

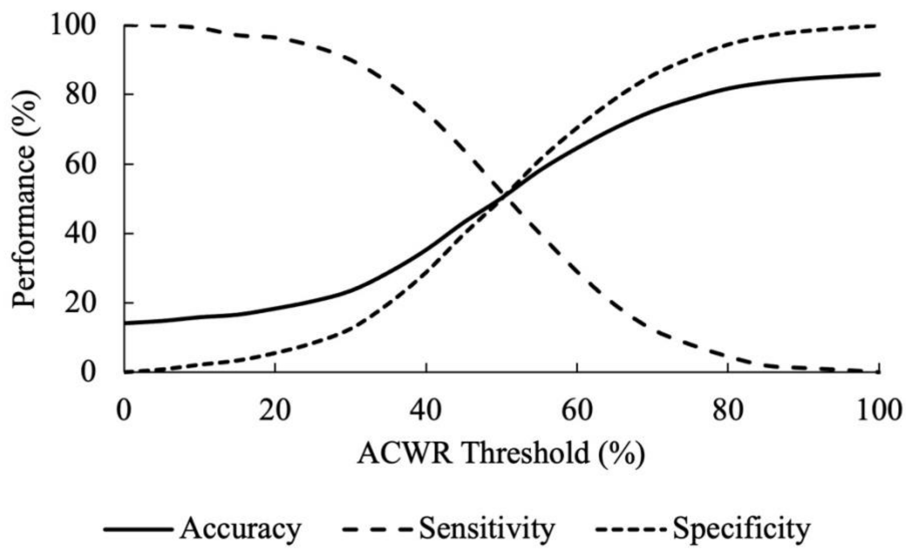

Figure 17. Accuracy, sensitivity, and specificity of an injury mitigation strategy with a varied ACWR threshold.

For Configuration A, each performance curve presented a sigmoid shape. When the ACWR threshold was initiated at 0%, all injuries were above the threshold where specificity, accuracy, and sensitivity were 0%, 14%, and 100%, respectively. Accuracy and specificity curves increased as the ACWR threshold increased, while sensitivity decreased. Greater changes in the curves generally occurred in the middle 30-70% of the ACWR threshold, which indicated most of the injuries were associated with ACWRs in that region. When the ACWR threshold reached 100%, all injuries were below the threshold where specificity, accuracy, and sensitivity were 100%, 86%, and 0%, respectively. Fanchini et al. and McCall et al. both showed similar low sensitivity and high specificity performance for strategies using session rate of perceived exertion as the input and ACWR thresholds based on an 85th percentile (Fanchini et al. 2018; McCall, Dupont, and Ekstrand 2018). Due the vast amount of IMS configurations possible, the performance curves of a given strategy should inform the ACWR threshold to optimize the strategy's impact or help determine whether the IMS should be used.

Figure 18 shows the injury likelihood profile of Configuration A.

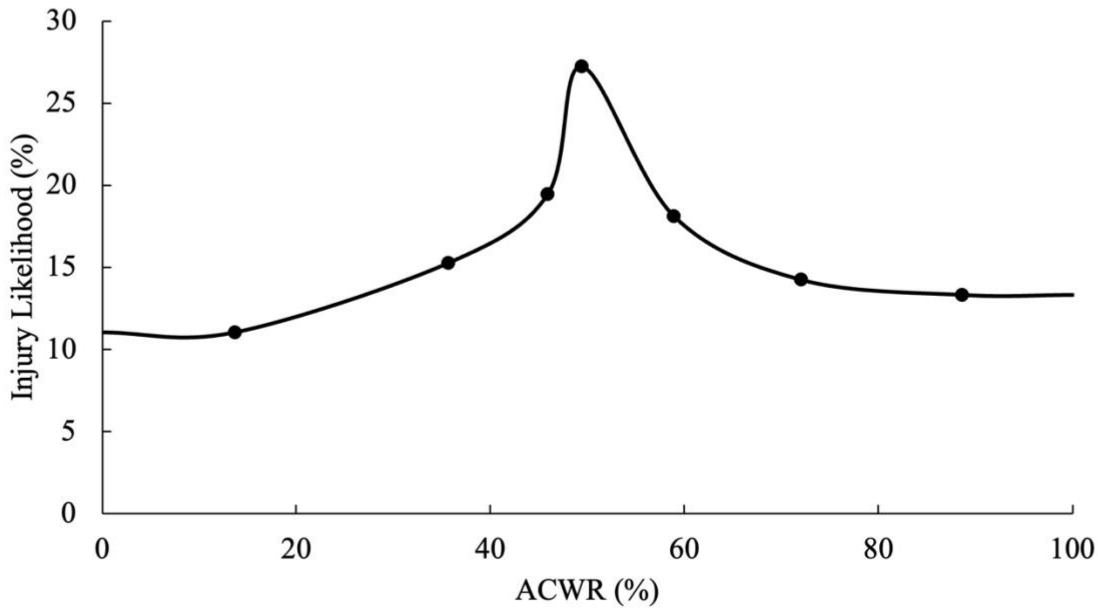

Figure 18. Injury likelihood profile for Configurations A.

The injury likelihood profile for Configuration A exponentially increased to a peak at approximately 50% of the ACWR spectrum followed by an exponential decrease. The likelihood of injury throughout the profile was within 10-30%. Studies have suggested injury likelihood and ACWR have a U-shaped relationship (Colby et al. 2017; Jaspers et al. 2018; Malone et al. 2017); however, the profile in Figure 18 suggests profiles do not universally have a U-shaped relationship. No studies were identified that have investigated the changes in an injury likelihood profile following interventions with an

ACWR-based IMS. It is possible the likelihood of injury may have had a U-shaped profile at one point but has since changed due to sport and performance development of the respective subjects. Consequently, an IMS should be developed using methods more specific to the relationship presented by the data, such as above or below an ACWR threshold or within or outside of an ACWR band, and those methodologies should be guided by the injury likelihood profile and IMS performance.

Injuries flagged and missed by Configuration A based on low, moderate, and high ACWR thresholds relative to injury category and season timeline are shown in Tables 23 and 24, respectively.

Table 23. Injuries flagged and missed by Configuration A by season timeline.

Time Period	n	25% ACWR Threshold			50% ACWR Threshold			75% ACWR Threshold		
		Flagged	Missed	Flagged (%)	Flagged	Missed	Flagged (%)	Flagged	Missed	Flagged (%)
Early September	14	13	1	93%	11	3	79%	3	11	21%
Late September	17	17	0	100%	17	0	100%	5	12	29%
Early October	20	20	0	100%	19	1	95%	10	10	50%
Late October	23	23	0	100%	22	1	96%	13	10	57%
Early November	12	12	0	100%	12	0	100%	5	7	42%

Table 24. Injuries flagged and missed by Configuration A by injury category.

Injury Category	n	25% ACWR Threshold			50% ACWR Threshold			75% ACWR Threshold		
		Flagged	Missed	Flagged (%)	Flagged	Missed	Flagged (%)	Flagged	Missed	Flagged (%)
All Injuries	86	85	1	99%	81	5	94%	36	50	42%
Strains	5	5	0	100%	5	0	100%	3	2	60%
Sprains	7	7	0	100%	7	0	100%	1	6	14%
Quadriceps	9	8	1	89%	8	1	89%	6	3	67%
Hamstring	13	13	0	100%	12	1	92%	4	9	31%
Glute	5	5	0	100%	5	0	100%	2	3	40%
Lower Back	5	5	0	100%	5	0	100%	3	2	60%
Hip	5	5	0	100%	5	0	100%	2	3	40%
Knee	8	8	0	100%	8	0	100%	3	5	38%
Ankle	8	8	0	100%	8	0	100%	3	5	38%

Relative to a seasonal timeline, the number of injuries within a time period increased as the timeline progressed and then decreased in early November, which corresponded with postseason activities. The number of missed injuries was affected by the threshold used, where at a high threshold there were relatively more injuries missed earlier in the timeline and more injuries flagged later in the timeline. Relative to each threshold, there were time periods with a similar number of flagged and missed injuries, such as in early and late September or early and late October for a high threshold. When considering the periodization of injury mitigation strategies, these grouped periods could identify time frames in which to focus certain mitigation efforts in addition to ACWR. Relative to injury categories, more injuries were generally missed than flagged at a high threshold. When considering specific categories, more sprain, hamstring, glute, knee, hip, and ankle injuries were also missed than flagged. Sprain and hamstring injuries had the most missed instances and may benefit from a tailored ACWR approach or alternative strategy that targets those specific injuries.

Approximately 45% of the recorded injuries occurred within the first 28 days of training and were not included due to the ACWR initialization phase. Both applications demonstrated an interaction between the injury lag period and the ACWR threshold, where the lag period and threshold could be optimized to maximize the impact of the strategy. More injuries were flagged relative to the injury category and seasonal timeline when the threshold was lower, and more injuries were missed as the threshold increased; however, the increase was not linear and did not correspond with the sensitivity of the IMS at the moderate and high ACWR threshold. A low threshold with longer lag period would likely flag more injuries than a high threshold with a short lag period due to more opportunities for an ACWR value to be above the threshold. However, practical considerations should be given to the loads needed to effectively develop athletes for competition. The interaction between lag period and threshold also demonstrated high ACWR values were the only mechanism detectable by the strategy. Alternative strategies would be needed to identify other mechanisms within and outside of the injury lag period, such as those leading to chronic injuries that may be impacted by loads outside of the lag period.

Conclusions

Despite the variations in ACWR and injury criterion methodologies, the performance of each configuration generally had high accuracy and specificity with low sensitivity when using an ACWR threshold optimized for peak accuracy. The methodologies included in this study are better suited for reactively monitoring and taking injury mitigation actions over proactively forecasting training and competition loads. However, further research is required to better understand how ACWR and injury criteria impact the effectiveness of an IMS. The injury likelihood profile, performance curves, and flagged injuries should be used to evaluate the type of criteria as well as the ACWR values associated with each criteria type. The optimization process for an IMS should consider thresholds associated with a submaximal accuracy in addition to the duration of the injury lag period.

CHAPTER 6

CONCLUSIONS

The purpose of this dissertation was to determine if ACWR should be integrated into an injury mitigation strategy (IMS) and, if so, what input, computation, and injury-related methodologies should be used with it. This dissertation concluded the inclusion of ACWR would provide information that could support injury mitigation decisions and efforts. However, the utility of ACWR depends on how it is applied, and there is not a universal configuration for its implementation. The methodologies selected for ACWR (i.e., injury definition, injury lag period, input, averaging method, coupling method, acute time frame, and chronic time frame) are significantly impacted by their interactions with the other methodologies selected, but the analytical results presented components for injury mitigation strategies, outlined in Figure 19, that can be developed in a hierarchical order.

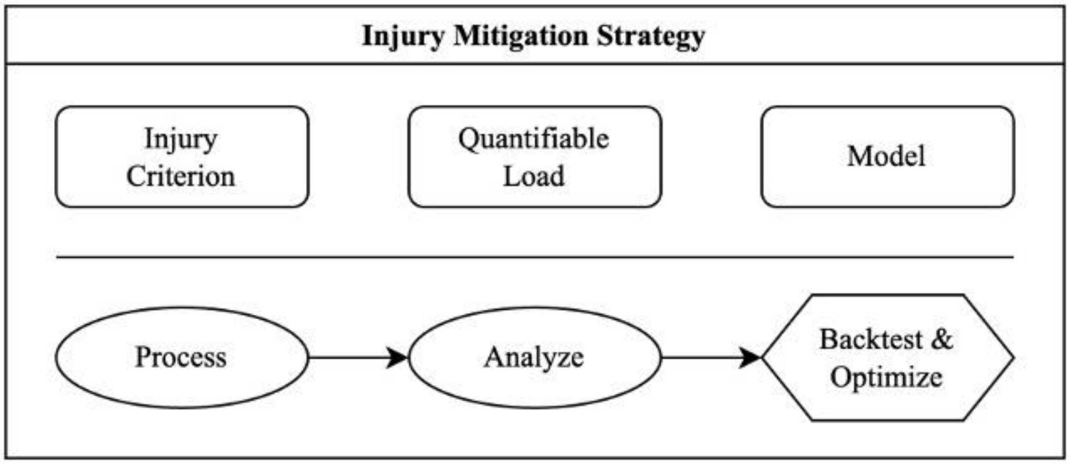

Figure 19. General framework for the development of injury mitigation strategies. The injury definitions and lag periods within the injury criterions had a more significant impact on the response variables within this dissertation than the GPS-based distances used to quantify training and competition loads. The input used with the ACWR models had a more significant impact than the averaging and coupling methods and acute and chronic time frames of the ACWR model. The development of injury mitigation strategies should initially investigate the injury criterion only and subsequently progress by integrating quantifiable loads and then models, while assessing the benefit and practicality of potential interventions at each stage. The progression also allows for the research and development of applicable data processing and analyzing methodologies. When analyses support further investigation of multiple options within a methodological component, all potential configurations can be backtested and variable parameters can be optimized to generate the best strategy that supports the needs of an organization.

Injury Criterion

The injury definition should be guided by the goals and objectives of a sport organization, and future research should investigate the processes for developing injury definitions relative to the needs of an organization. The definition used establishes the number of injuries available for an analysis based on features associated with an injury or group of injuries and influences whether a strategy should be mechanistically or statistically driven. Injury features should be purposefully grouped together until there is an adequate number of injuries for the subsequent analytical methods, and a statistical approach could be taken when there are not enough injuries for a mechanistic approach. Features could be based on characteristics that describe specific injuries, athletes, contexts, and other aspects related to specific needs. In addition to the time-loss aspects in the literature, injury characteristics could be described by tissue type, biomechanical movements, local to global areas, and others. Athlete characteristics could include position, role, performance profiles, and others. Contextual characteristics could consist of activity type, periodization phases, and others.

The injury lag period should be related to the underlying injury mechanisms of the injury definition, when possible. However, it may be more practical to determine the lag period by minimizing its duration relative to a desired outcome within an optimization process. The specific ACWR strategy criteria, number of injuries included, and input and computational component effects also contribute to the outcomes of an IMS and should be considered when evaluating the lag period.

Quantifiable Load and Computational Model

The input used within an IMS should also be related to the underlying injury mechanisms of the injury definition, when possible. The input and model components had consistent dependencies on each other between different applications, so the methodologies selected after the definition and related inputs should be evaluated together. Due the plethora of options within the methods required to develop an IMS, all options within each component should be analytically reduced by identifying and removing those that have an effect that is not different from others on the response variable of interest. When the remaining options interact within a given configuration, the configurations may further be reduced by analyzing and removing those that have an effect that is not different from others; though, alternative analytical techniques may be required to converge on fewer configurations. Subsequently, all remaining or selected IMS configurations should then be backtested and optimized to determine the best strategy to implement. Further research is needed for the appropriate criteria of pursuing backtesting and optimization in injury applications. However, considerations should be given to the magnitudes and patterns within different approaches, such as thresholds, bands, accumulated differences, etc., and those approaches should be guided by characteristics of the strategy, such as injury likelihood profiles, performance curves, and flagged injuries.

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