Training Load and Injury in Professional Ballet

A thesis submitted by

Joseph W. Shaw

For the award of
Doctor of Philosophy

St. Mary's University, Twickenham
Faculty of Sport, Allied Health, And Performance Science
2022

ABSTRACT

Training Load and Injury in Professional Ballet

Joseph W. Shaw
St. Mary's University, Twickenham

Doctor of Philosophy

In professional ballet, training load has frequently been suggested to be associated with the risk of musculoskeletal injury. Despite a recent surge in the number of training load research studies in high performance sport, relatively little research has been conducted investigating training load in ballet. The aim of this thesis was, therefore, to describe the training loads undertaken by professional ballet dancers, explore the load-injury relationship in ballet, and provide valid methods and recommendations for load management in professional ballet.

Two five-season cohort studies were conducted, investigating scheduling and medical data at an elite professional ballet company. Shared frailty models were used to investigate relationships between individual risk factors, accumulated dance volume, and hazard ratios for injury risk. Greater week-to-week changes in dance volume and smaller seven-day dance volume were associated with increase rates of overuse injury, whilst age (traumatic injury), previous injury, and company rank (overuse injury) were also associated with increases in hazard ratios for injury. Analyses of scheduling data were consistent with previous research regarding the large rehearsal and performance volumes completed by ballet dancers. For the first time, however, the present research revealed the large variation in dance hours occurring from week-to-week, across the season, and between company ranks. In professional ballet, there is great scope to optimise training loads from increased emphasis on periodisation of the repertoire and rehearsal schedule alone.

Three methodological studies explored the development and validation of training load measures in professional ballet. Firstly, the validity of session rating of perceived exertion in professional ballet dancers was investigated, revealing very large positive linear relationships with Edwards and Banister training impulse scores. Correlation coefficients were comparable across men and women, though were larger in rehearsals compared with ballet class. Secondly, a rule-based classifier for measuring jump frequency and height from accelerometer data was developed and validated, demonstrating a high degree of accuracy, and providing a simple means of managing jump load. Finally, a series of recurrent neural networks were developed to facilitate the measurement of tissue-specific forces outside of a laboratory using inertial measurement units, outperforming single variable linear regression approaches for the measurement of Achilles tendon, patellar tendon, and tibial force. Open-source software was developed and presented to house these algorithms, and database and visualize longitudinal training load data.

This thesis demonstrates the importance of managing a rehearsal and performance schedule throughout a professional ballet season. Where more in-depth understanding of training load is required for managing high-risk dancers, this thesis provides practical, valid, and open-source methods for quantifying load.

Publications

Shaw JW, Springham M, Brown DD, Mattiussi AM, Pedlar CR, Tallent J. (2020) The Validity of the Session Rating of Perceived Exertion Method for Measuring Internal Training Load in Professional Classical Ballet Dancers. *Frontiers in Physiology.* 11(480).

Shaw JW, Mattiussi AM, Brown DD, Williams S, Kelly S, Springham M, Pedlar CR, Tallent J. (2021) Dance Exposure, Individual Characteristics, and Injury Risk over Five Seasons in a Professional Ballet Company. *Medicine & Science in Sports & Exercise.* 53(11):2290-2297.

Shaw JW, Mattiussi AM, Brown DD, Springham M, Pedlar CR, Tallent J. (2021) The Activity Demands and Physiological Responses Observed in Professional Ballet: A Systematic Review. *Journal of Sport & Exercise Science.* 5(4):254-269.

Shaw JW, Mattiussi AM, Brown DD, Williams S, Springham M, Pedlar CR, Tallent J. (In Press) Rehearsal and Performance Volume in Professional Ballet: A Five-Season Cohort Study. *Journal of Dance Medicine & Science.*

Related Publications

Mattiussi AM, Shaw JW, Williams S, Price PD, Brown DD, Cohen DD, Clark R, Kelly S, Retter G, Pedlar C, Tallent J. (2021) Injury epidemiology in professional ballet: a five-season prospective study of 1596 medical attention injuries and 543 time-loss injuries. *British Journal of Sports Medicine.* 55:843-850.

Mattiussi A, Shaw JW, Brown DD, Price P, Cohen DD, Pedlar CR, Tallent J. (2021) Jumping in Ballet: A Systematic Review of Kinetic and Kinematic Parameters. *Medical Problems of Performing Artists.* 36(2):108-128.

Peer Reviewed Presentations

Mattiussi AM, Shaw JW, Williams S, Price PD, Brown DD, Cohen DD, Clark R, Kelly S, Retter G, Pedlar C, & Tallent J. (2021) Injury Epidemiology in Professional Ballet: A Five-season Prospective Study of 1596 Medical Attention Injuries and 543 Time-loss Injuries. *European College of Sports Science Congress 2021*.

Shaw JW, Mattiussi AM, Brown DD, Springham M, Pedlar CR, & Tallent J. (2021) The Demands of a Professional Ballet Schedule: A Five-Season Study. *BASES Conference 2021*.

Mattiussi AM, Shaw JW, Williams S, Price PD, Brown DD, Cohen DD, Clark R, Kelly S, Retter G, Pedlar C, & Tallent J. (2021) Injury Epidemiology in Professional Ballet: A Five-season Prospective Study of 1596 Medical Attention Injuries and 543 Time-loss Injuries. *BASES Conference 2021*.

ACKNOWLEDGMENTS

I would like to thank the following people who have assisted me throughout this PhD:

Firstly, I must express my immense gratitude to my supervisory team: Dr Jamie Tallent, Professor Charles Pedlar, Dr Matthew Springham, and Dr Derrick Brown. Your diligent support has meant that I never once felt lost throughout this process, whilst your honesty, trust, and humour have made this an overwhelmingly enjoyable experience.

I am equally grateful to Adam Mattiussi, with whom I've had the pleasure of sharing this journey. The countless messages, calls, and conversations have probably made this work twice as good as it otherwise would have been, and they've certainly made it twice as fun. Thanks for everything mate.

I have also had the privilege of receiving additional guidance from Dr Daniel Cleather, Dr Alexandra Atack, and Dr Sean Williams. Thank you for sharing your time and expertise; I consider myself extremely fortunate to have had the opportunity to learn from each of you.

I would like to thank Greg Retter for giving me the opportunity to undertake this project, as well as Richard Clark and Shane Kelly for continuing to support my work throughout these past few years. It has been a joy to work as part of this team, and I can't express my thanks enough to Brian, Gregor, Rob, Gemma, Jane, Fiona, Konrad, and so many others, for welcoming me, and helping out along the way.

To the staff and artists of The Royal Ballet, I am so grateful for your engagement and interest in this project. It has truly been an immeasurable pleasure to spend the past three years working with you.

Finally, to my friends and family. For your love and support, I am eternally grateful.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF APPENDICES

LIST OF ABBREVIATIONS

HR	Heart rate
RPE	Rating of perceived exertion
s-RPE	Session rating of perceived exertion
[BLa]	Blood lactate concentration
TRIMP	Training impulse
b-TRIMP	Banister training impulse
e-TRIMP	Edwards training impulse
l-TRIMP	Lucia training impulse
i-TRIMP	Individualised training impulse
m-TRIMP	Modified training impulse
AUs	Arbitrary units
d-RPE	Differential session rating of perceived exertion
IMU	Inertial measurement unit
ACWR	Acute:chronic workload ratio
HARKing	Hypothesizing after results are known
$\dot{V}O_2$	Oxygen uptake
$\dot{V}O_{2max}$	Maximal oxygen uptake
MMAT	Mixed methods appraisal tool
BMI	Body mass index
CI	Confidence interval
DOF	Degrees of freedom
MAE	Mean absolute error
TP	True positive
FP	False positive
FN	False negative
LoA	Limits of agreement
RMSE	Root mean square error
SQL	Structured query language

CHAPTER 1

Introduction

1.1 Context

1.1.1 A History of Classical Ballet

Ballet is a form of performance art through which dancers may portray an emotion, express an idea, or convey a narrative through dance. The origins of ballet can be traced back to the Italian Renaissance, where dances would be performed in the royal courts during formal events and celebrations [1]. In the 16$^{\text{th}}$ century, the marriage of Catherine de' Medici to King Henry II brought ballet to France [1]. It was in France, in the 17$^{\text{th}}$ century, that the art became formalised, developing its own vocabulary and technique. King Louis XIV founded the *Académie Royale de Danse*, the first formal ballet organisation, and had his ballet instructor Pierre Beauchamp codify the art form [1]. The spread of ballet in the 19$^{\text{th}}$ and 20$^{\text{th}}$ centuries, firstly across Europe, and subsequently the rest of world, led to the emergence of more professional companies and teaching methods [1].

1.1.2 Ballet Technique

The formalisation of ballet brought with it the development of ballet technique, governing the movement and form of dancers. Whilst variations exist between teaching methods, the underlying foundations of ballet technique remain constant [2]. These include: *posture* (or *alignment*)—the integration of the whole body to form a cohesive whole, such that a vertical line can be drawn from the head, down through the torso, pelvis and the feet; turn-out—the external rotation of the leg, from the hip; *placement*—the positioning of each body part, throughout movement, such that its natural relationship with others is maintained; and *lengthening* (or *extension*)—elongation of the limbs through extension of the joints [2].

1.1.3 Long Term Development of Ballet Dancers

Many dancers will begin learning ballet at a young age, often leaving home at the age of 11 to begin full-time training alongside academic classes [3]. Following graduation from a ballet school, classical dancers may seek employment from a professional company. The career of a dancer begins in the *corps de ballet*, for which roles are typically performed as part of an ensemble. As their career progresses, a dancer may be promoted to the rank of soloist, performing solo or supporting roles in a production. Finally, a selection of dancers will reach the rank of principal—the most senior artistic rank—performing leading roles in the company's productions.

For classical dancers employed by resident companies (i.e., not touring companies), a dancer's day-to-day schedule is relatively consistent in its structure. The day typically begins with ballet class: a 60–90 min session where dancers can hone their technique, featuring a progression in both physical and technical intensity as dancers move from exercises at the *barre* (stationary exercises supported by a handrail), to *adagio* exercises in the centre of the studio, progressing to *petit allegro* and finally, more explosive *grand allegro* exercises across the studio [4]. Following ballet class, dancers complete rehearsals: sessions during which they will be learning or practicing choreography for a specific ballet. On any given day a company may also perform for a public audience, either during the day (a *matinée*) or in the evening [5]. Performances, typically ~3 h in duration with intervals, may be comprised of a single full-length ballet (e.g., Romeo and Juliet, The Nutcracker, etc.), or several shorter ballets.

1.2 Science and Medicine Support in Ballet

The activity profile of ballet is intermittent [6]; dancers complete high intensity explosive movements interspersed with movements requiring fine motor control, and periods of rest or low intensity activity. In recent years, the physical demands of professional ballet have been increasingly recognised, with dancers having been termed 'performing athletes' in sports medicine research [7]. To this end, many of the foremost ballet companies and schools now house sports science and medicine departments—comparable to those seen in elite sports teams—providing services such as physiotherapy, strength and conditioning, Pilates, and performance nutrition. Nonetheless, both the provision and uptake of science and medicine in dance, as well as the research underpinning these services, currently trails that observed in sport [8].

One area of sports medicine research that has grown vastly in recent years is training load, and its relationships with athletic performance and health [9, 10, 11]. For those working in professional ballet, it is well-known that the rehearsal and performance schedules undertaken by dancers impose considerable physical and cognitive stress [12, 13]. However, research into the training load demands of professional ballet, and its implications for dancer health and performance, is scant. Some limited evidence, though, is sufficient to warrant further research: dancers engage in > 5 h.day^{-1} of dance [5]; companies perform ~140 shows per season [14]; and 68 and 60% of injuries, in women and men, respectively, are overuse in onset [15].

1.3 Thesis Aims

Some limited low-level or anecdotal evidence suggests that the training loads undertaken by professional ballet dancers are high in comparison to those seen in sportspeople. Several research groups have suggested that these training loads are associated with injury risk, and thus require careful management. To date, however, research describing training loads in ballet, investigating the relationships between training loads and injury in ballet, or validating methods for quantifying training load, is extremely limited.

Three broad aims will, therefore, guide this thesis:

1. To understand the training load demands experienced by professional ballet dancers.

2. To explore the relationship between training load and musculoskeletal injury in professional ballet.

3. To investigate the validity and reliability of measures of internal and external training load, and provide professional ballet companies with practical tools and best practice recommendations for the management of training load.

Chapter 2 will review current literature in the field of training load in sport and dance, following which these broad thesis aims will be refined into specific research questions. These research questions, as well as an overview of the thesis structure, are presented at the conclusion of Chapter 2.

CHAPTER 2

The Quantification and Implications of Training Load in Sport and Dance: A Literature Review

2.1 Outline

This chapter reviews and summarises training load research in sport and dance. Firstly, this review covers and defines concepts underpinning the quantification and manipulation of training; methods of training load quantification are then discussed and critiqued; an overview of load-injury research is presented, and specifically the methodological issues observed in longitudinal load-injury research; and finally, the current body of training load injury in dance is reviewed, both in terms of methodological approaches to training load quanification, and existing load-injury research. Research into the specific activity demands and physiological responses observed in professional ballet is covered in the systematic review presented in Chapter 3.

2.2 Context

Increasing training volume and training intensity is desirable to athletes and sports teams seeking to elevate their performance level above that of their competitors [16]. Similarly, in professional ballet, greater training volumes and intensities allow dancers and companies to continually hone the execution of movements and choreography, and subsequently amass artistic esteem, career success, and financial rewards. Whilst effective prescription of training provides a means by which athletes and dancers can improve their performance, inappropriate management of training load may result in adverse outcomes such as overtraining syndrome, illness, and injury [17]. The ability to quantify training stress, and understand the relationship between training stress and the resulting adaptive or maladaptive response is, therefore, of primary interest to athletes and dancers, and their coaches

[17].

2.2.1 Defining Training Load

Load has been used as a global term encapsulating the cognitive and physiological stress experienced by an individual [18]. The load experienced by an athlete is not limited to the stress resulting from participation in athletic training or competition, but also extends to further psychosocial stress resulting from lifestyle factors such as an athlete's personal life, travel requirements, or academic commitments [19].

Training load can be defined as a training or competition-induced input variable which elicits a psychophysiological response [20]. Training load is the parameter which the coach attempts to manipulate to stimulate physiological adaptation; Coutts et al., [21] therefore, suggest that the quantification of training load forms the basis of any athlete monitoring system. Measures of training load can be either external or internal [18]. External training loads relate to the physical work which is performed during an exercise bout; for example, the number of sets or repetitions of an exercise, the distance travelled, the weight lifted, or the speed of movement [18]. Given its relative simplicity to measure in practice [19], training is commonly prescribed in terms of the external training load, with the aim of manipulating an athlete's internal training load. Internal training loads are those which are measured internally to the athlete, quantifying a tissue or system's response to an external load; for example, heart rate (HR), session rating of perceived exertion (s-RPE), or blood lactate concentration [BLa] [18]. Thus, two athletes may undertake identical external training loads, yet incur different internal training loads. Importantly, it is the internal training load, and not the external training load, that provides the stimulus for physiological adaptation.

2.2.2 The Training Process

The training process is underpinned by the concept of adaptation [22]. Training is designed to impose stress, offsetting the body's homeostasis, and provoking a transient physiological response. An acute reduction in neuromuscular performance is, therefore, observed after the application of a training stimulus; following a period of recovery, however, a supercompensation effect occurs, such that a subsequent training bout of an equal magnitude would not offset homeostasis to the same extent (Figure 2.1 A) [23]. The repetition of a physiological stress over time stimulates a chronic adaptive response, leading to semi-permanent physiological changes. Should rest and recovery be insufficient following a training bout, an athlete's capacity for load will instead be reduced as further training stress is applied,

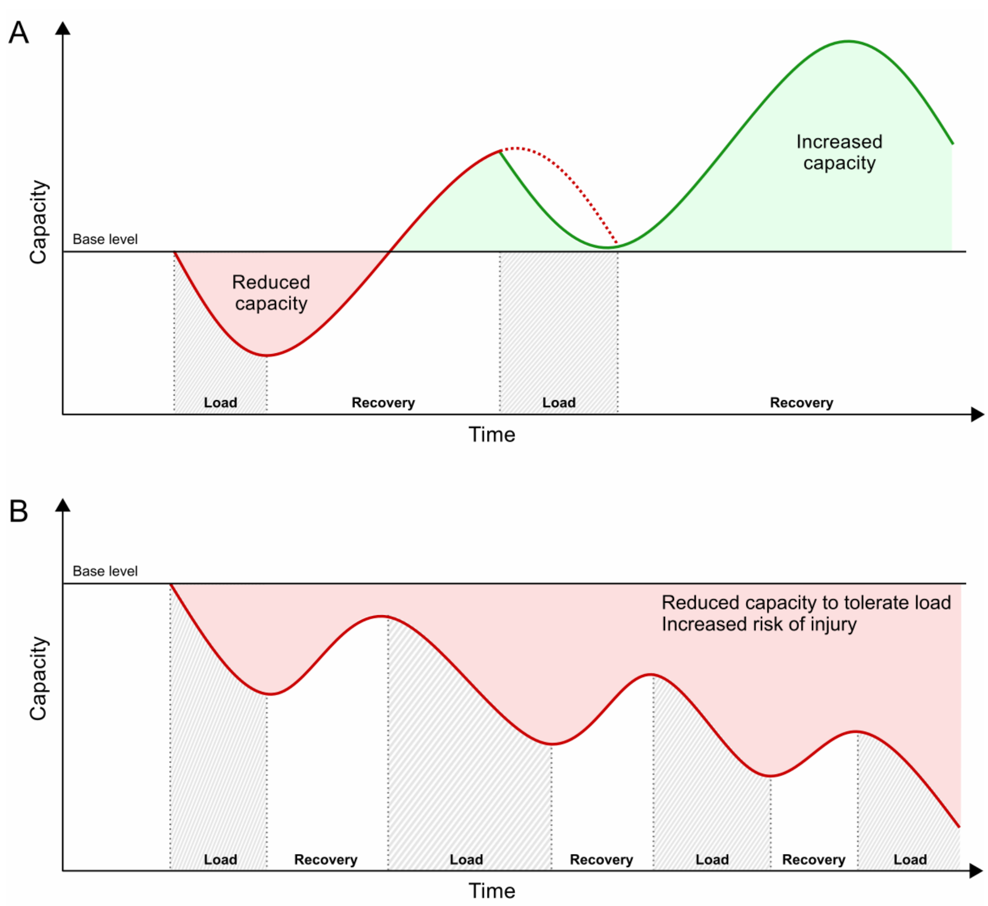


Figure 2.1: A) Biological adaptation and B) biological maladaptation through cycles of loading and recovery. Redrawn from Soligard et al. [17]

ultimately resulting in maladaptive responses (Figure 2.1B).

The relationship between load and athlete health has been conceptualised as a well-being continuum (Figure 2.2) [23]. The application of load results in a rightward shift along the continuum, whilst a period of recovery results in a leftward shift. When load is prescribed appropriately, homeostasis is offset such that an acute performance decrement is seen lasting days to weeks, followed by a supercompensation effect and a performance improvement; a process referred to as *functional overreaching*. Conversely, when further loading stimuli are applied before sufficient recovery, *non-functional overreaching* may occur, whereby the neuromuscular performance decrement may extend from weeks to months; whilst full recovery may be achieved, no supercompensation effect is observed. Also included in the wellness continuum are clinical pathologies, such as *clinical symptoms*, *overtraining syndrome*, *time-loss injury,* and *illness*, which may diminish performance for longer periods, or force the cessation of further loading [17].

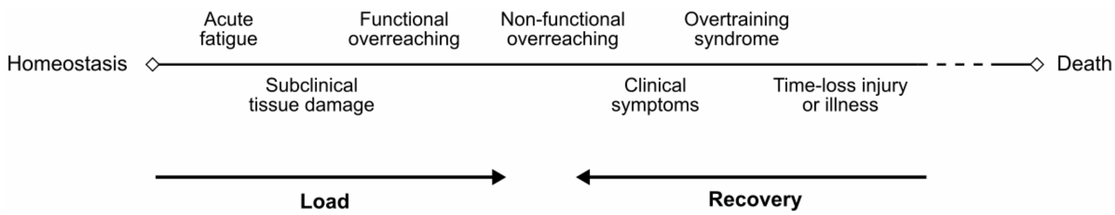


Figure 2.2: Well-being continuum. Redrawn from Soligard et al. [17], based on the original work of Fry et al. [23].

The physical states along the wellbeing continuum are not discrete events, but instead, represent a gradual transition in performance and wellbeing. Thus, neither the manipulation of an athlete's status nor the identification of their exact status at any given time is straightforward. Furthermore, an athlete does not need to undergo each physical state in turn; for example, time-loss injury may occur before the onset of non-functional overreaching [17]. Finally, it should also be recognized that movement across the continuum is not dictated by training load alone, but is a result of the interplay between training load and non-sport stress placed on the athlete. For example, lifestyle factors such as sleep, nutrition, travel, personal relationships, psychological stress, etc., may all contribute to an athlete's state of wellbeing. It is, therefore, important that coaches account for all types of load when planning training and recovery.

2.2.3 Training and Performance

The understanding that the manipulation of an athlete's training load can bring about changes in their physical status is not a new concept. Calvert et al. [24] presented a systems model of the effects of training on physical performance, whereby performance (p(t)) is determined by the interplay between fitness and fatigue, determined by the equation:

$$p\,(t) = [(e^{\frac{-t}{\tau_1}} - e^{\frac{-t}{\tau_2}})\ - Ke^{\frac{-t}{\tau_3}}]{*}w(t)$$

Where K is a constant adjusting the magnitude of the fatigue response in relation to the fitness response, τ_1 and τ_2 are time constants associated with the calculation of fitness (50 and 5 days, respectively, in Calvert et al. [24]), τ_3 is a time constant associated with the calculation of fatigue (15 days in Calvert et al. [24]), w(t) is the training impulse, * represents convolution, and t indicates the day of the training impulse. Following its initial publication, Banister's group updated their model, removing the second fitness parameter which was not supported by their data, such that fitness (g(t)) and fatigue (h(t)) are modelled as:

$$g(t) = g(t-i)\, e^{\frac{-i}{\tau_1}} + w(t)$$

and

$$h(t) = h(t-i)\, e^{\frac{-i}{\tau_2}} + w(t)$$

where i is the duration since the previous training session, and τ_1 and τ_2 are the decay constants for each input. Performance is subsequently calculated as the difference between fitness and fatigue, adjusted for weighting factors. Thus, the idea that a bout of training can bring about both positive and negative adaptations is well established in the literature.

2.2.4 Principles of Training

In an effort to ensure the training process elicits the desired adaptations, coaches are guided by common principles [25]:

- *Specificity* – the movement patterns and intensity of the training stimulus should target a specific task or component of fitness/performance.
- *Overload* – the training stimulus imposed on an athlete must be greater than that to which the athlete is already accustomed.
- *Progression* – over time the training stimulus must gradually increase, such that overload is maintained throughout a training programme.
- *Reversibility* – following the removal of a training stimulus, training adaptations will be lost over time.
- *Periodization* – a planned and systematic variation in training to target differing physiological adaptations, and mitigate the risk of illness, injury, and overtraining.
- *Rest and Recovery* – an appropriate period of offload should be given to allow necessary recovery and adaptation to take place.

Furthermore, the type and magnitude of training adaptations are dependent on the training stress imposed. Training load itself may, therefore, be manipulated by four further principles [26]:

- *Frequency* – the number of training sessions in any given period.

- *Intensity* – the exertion of any given physiological system required to complete the exercise.
- *Duration* – the length of time which the exercise or training session lasts.
- *Modality* – the nature of the exercise(s) being performed.

2.3 Quantifying Training Load

To effectively plan and evaluate training programmes, it is important that sports science and medicine practitioners possess a valid and reliable means of quantifying training load. There is no universal gold standard measure of training load; instead, the method should be specific to the activity in question [18]. For example, HR may be an appropriate measure of metabolic load during endurance cycling, but is less relevant during heavy resistance training. The following section is not an exhaustive list of methods used for the quantification of load, but instead details common methods used in sport.

2.3.1 Internal Training Load

2.3.1.1 Heart Rate

Heart rate monitoring provides science and medicine practitioners with a non-invasive and objective means of measuring an athlete's cardiovascular response to exercise. At any given moment, HR provides a snapshot into the metabolic intensity experienced by an athlete [27]. The affordability of HR monitors, and their relatively small impact on comfort and movement make them a practical tool for monitoring internal training load in field settings.

At the most basic level, HR is used in field settings to measure and manipulate exercise intensity. Exercise intensity domains [28] can be determined through an incremental exercise test, and subsequently used to guide the intensity of training. For example, identification of the HR at which more meaningful physiological responses occur (e.g., blood lactate thresholds, oxygen uptake kinetics) allows the practitioner to accurately manipulate training intensity without the need for invasive or impractical measures [29]. Following a training or competition session, HR data may be used to calculate training load variables; this may be as straightforward as calculating an athlete's mean HR during a session or drill. More commonly, however, training load is calculated as the product of volume (session duration) and intensity (HR) [24].

Morton et al. [30] identified HR and session duration as variables which when considered together, explain much of the training stimulus incurred during a session. The concept of a training impulse (TRIMP) was, therefore, proposed to quantify the training load incurred during a specific session or drill as a single value:

$$TRIMP = exercise\ duration\ \ (\Delta HR\, ratio)\ \mathrm{Y}$$

where HR ratio is defined by the formula:

$$HR\, ratio = \frac{\mathrm{HR_{ex}} - \mathrm{HR_{rest}}}{\mathrm{HR_{max}} - \ \mathrm{HR_{rest}}}$$

where HR_{ex} is the mean HR rate during exercise, HR_{rest} is the athlete's resting HR, and HR_{max} is the athlete's maximal HR; and where Y is defined by the formula:

$$Y = e^{\mathrm{bx}}$$

where b is a weighting factor of 1.92 for males or 1.67 for females, and x is the HR ratio; accounting for the exponential rise in blood lactate concentration observed with progressive exercise intensity, and the differences in this curve across sexes. This method is henceforth referred to as b-TRIMP.

The TRIMP concept has since been simplified by Edwards [31] (e-TRIMP), using five HR zones (50–60%, 60–70%, 70–80%, 80–90%, and 90–100% $\mathrm{HR_{max}}$); the duration spent in each zone is multiplied by a scaling factor (1, 2, 3, 4, and 5, respectively), following which each value is summated to calculate the e-TRIMP. The e-TRIMP calculation may better account for changes in intensity in intermittent activities, where a mean HR may not give an accurate representation of the metabolic load experienced by the athlete. Similarly, for professional cyclists, Lucia et al. [32] proposed a system based on intensity zones, though in this instance three zones were used, delineated by the ventilatory threshold and the respiratory compensation point (l-TRIMP).

Manzi et al. [33] demonstrated that should it be practical to conduct a maximal incremental test before exercise, an individualised version of TRIMP (i-TRIMP) may provide a greater degree of validity. The i-TRIMP method has two improvements over the original: firstly, it uses an individualised weighting factor based on each athlete's blood lactate curve; and secondly, rather than use the athlete's mean HR, a TRIMP value is calculated at each HR measurement during the session, and thus accounts for sessions of variable intensity. In the absence of individualised blood lactate curves a modified TRIMP method (m-TRIMP), using the generic weighting factor from b-TRIMP, but the timepoint-specific calculation from i-TRIMP, may nonetheless represent an improvement on b-TRIMP for intermittent exercise [33]:

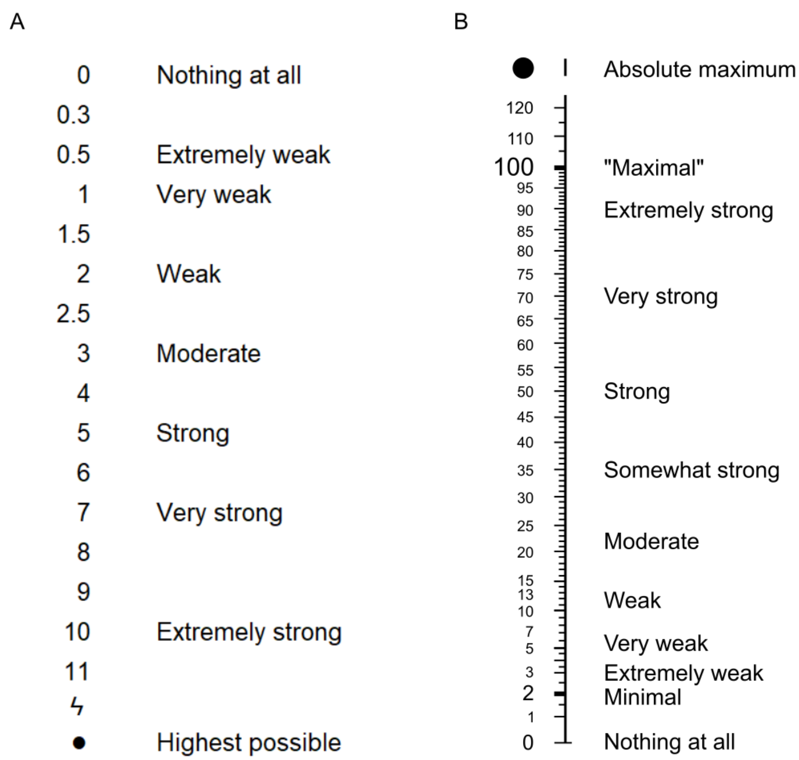


Figure 2.3: A) Borg CR-10 scale and B) Borg CR-100 scale.

$$m\text{–}TRIMP = \sum HR\,ratio\ \times duration\ \times\ e^{\mathrm{bx}}$$

where b is a weighting factor of 1.92 for males or 1.67 for females, and $\chi$is the HR ratio.

2.3.1.2 Session Rating of Perceived Exertion

Foster et al. [34] proposed the s-RPE, extending the conceptual basis of TRIMP (i.e., duration × intensity) to use with an athlete's rating of perceived exertion (RPE). Session-RPE is calculated by multiplying the session duration by the athlete's RPE—typically measured using Borg's CR-10, a category-ratio scale anchored at the number 10 [35] (Figure 2.3 A)—to provide a training load value measured in arbitrary units (AUs). Since its inception, s-RPE has been validated in numerous sports, against several criterion measures of internal load, for example, b-TRIMP [36, 37, 38], e-TRIMP [36, 37, 38], l-TRIMP [36, 38], and blood lactate concentration [37, 39].

Several alterations to the methodology of s-RPE have been suggested to increase the degree to which the measurement accurately reflects a physiological construct. The use of a CR-100 scale (Figure 2.3 B) instead of a CR-10 scale, may provide a greater degree of sensitivity to small differences in exertion, and avoid directing athletes toward ratings associated with verbal anchors [40]. Differential s-RPEs (d-RPE) have been proposed to increase the specificity of the load construct being measured, by asking the athlete for separate RPEs for key sensory inputs, for example, central and peripheral exertion [41]. For example, a "very hard" RPE may be given in response to both a continuous bout of cycling exercise and a resistance training session, though the physiological responses are likely to differ considerably.

2.3.2 External Training Load

2.3.2.1 Manual Observation of Volume or Intensity

In several sports, some level of external training load can be quantified through simple observation. At the most basic level, the duration of an exercise bout or the number of exercise bouts can serve as an approximation of external load. In some instances, the structure of the activity itself may facilitate a straightforward means of quantifying training volume; for example, in baseball, a pitcher's load may be quantified via the number of pitches thrown [42], whilst in cricket, a bowler's load may be reasonably accurately quantified via the number of overs bowled [43]. In sports such as weightlifting, both the volume and intensity of the activity are inherent in the training programme itself through the repetitions performed and the weight lifted. Similarly, in running events, volume and intensity are evident from the distance travelled, and the pace of the run. Finally, when practitioners have the available time and high levels of detail are required—particularly in complex open sports—time motion and video analysis may provide further insight into the demands of an activity. Time motion and video analysis, for example, has been used to calculate work-to-rest ratios, movement intensities, and the frequencies of sport or dance-specific actions [44, 45, 46].

2.3.2.2 Inertial Measurement Units

Inertial measurement units (IMUs) house accelerometers, gyroscopes, and sometimes magnetometers, measuring the linear acceleration, angular velocity, and orientation of a body, respectively [47]. An IMU typically contains three of each device; one aligned to each of the x, y, and z axes. The integration of angular velocity to calculate orientation, and the double integration of linear acceleration (following the subtraction of gravity) to calculate displacement, can, therefore, be used to locate the position of the IMU relative to a known point in space; a process known as *dead reckoning* [48].

Whilst dead reckoning using accelerometers and gyroscopes alone is theoretically viable, errors in the measurements of linear acceleration and angular velocity lead to inaccuracies in position estimation [48]. Measurement error is in two primary forms: bias and noise [48]. Since position at each time point is calculated relative to the previous time point, measurement errors are cumulative. As a result, bias in the measurement of angular displacement, being the first integral of angular velocity as a function of time, therefore, increases linearly with time (Figure 2.4 A); bias in displacement, being the second integral of acceleration as a function of time, will, therefore, increase exponentially with time (Figure 2.4 B). The presence of random noise results in *random walk* (Figure 2.4 C). In other words, in the absence of bias, the error follows a normal distribution around the mean, however, it is not possible to predict the direction of this error during a single measurement. To garner accurate positional data over long periods, IMU data are combined with other positional data sources which do not suffer from measurement drift [48]. To calculate accurate orientation, IMUs are often combined with magnetometer data, whilst to calculate position, IMU data may be combined with global positioning systems, camera, or ultra-wideband data.

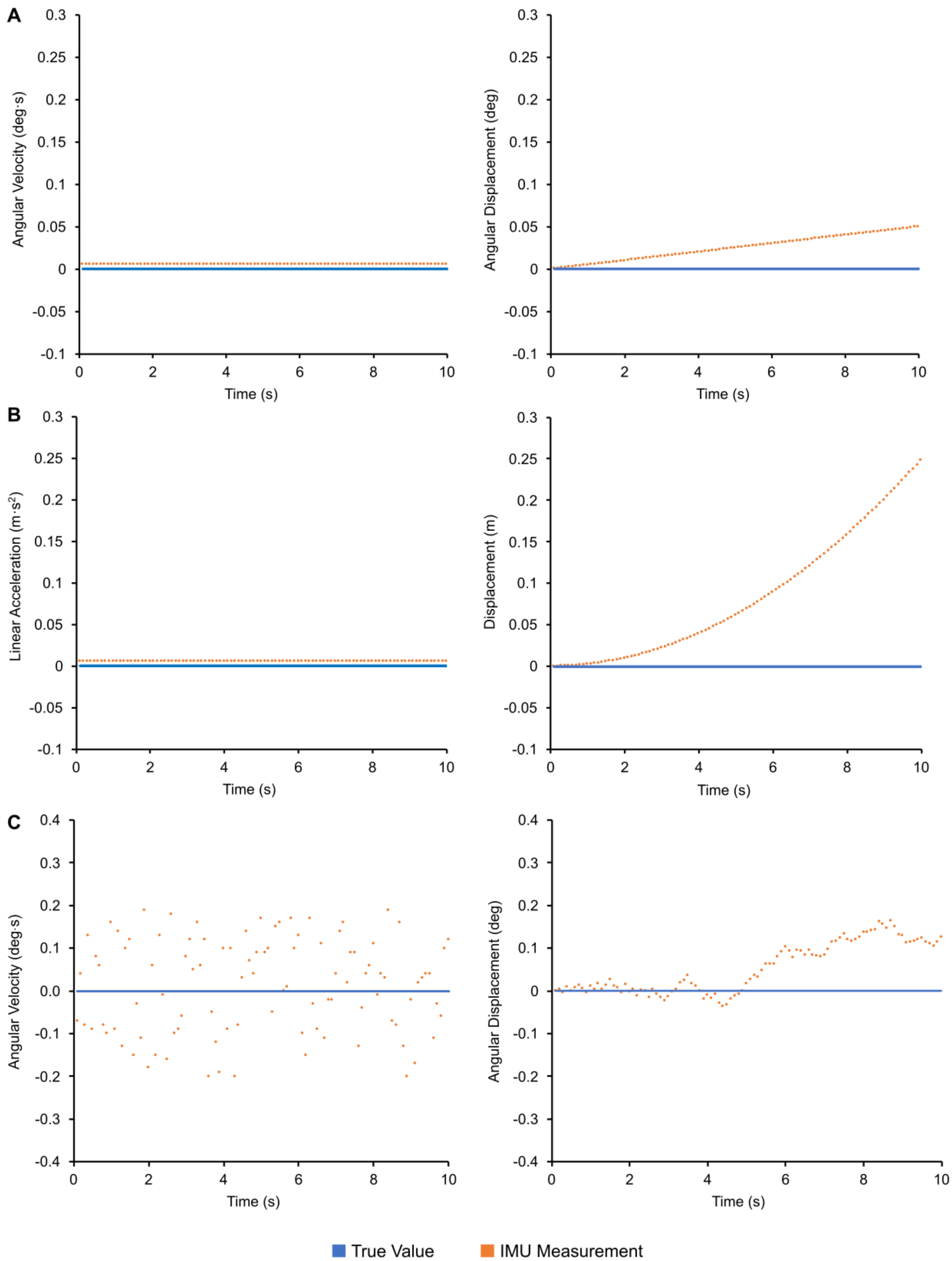


Figure 2.4: Sources of inertial measurement unit error. A) Constant drift resulting from integration of a signal with a constant bias. B) Exponential drift resulting from double integration of a signal with a constant bias. C) Random walk resulting from a signal subject to random noise.

In physical activity and health research, accelerometers have long been used to quantify energy expenditure [49]. Whilst the use of accelerometers and IMUs is historically less common in sporting research, their applications have been wide-ranging; for example, to quantify the magnitude of head impacts [50], the forces of punches and kicks [51], and intra-stroke kayak velocity [52]. In training load research, studies using accelerometers and IMUs typically fall into one of three categories. Firstly, IMUs have been used to aid in the identification of specific actions during training or competition; for example, machine learning approaches have been used to monitor shot types and counts in badminton [53] and tennis [54], and jump counts during figure skating [55]. Secondly, whole-body movement demands have been quantified through variables such as *accelerations*, *decelerations*, *high metabolic load*, *PlayerLoad*™, and *collisions* [56, 57]. Finally, the kinetics and kinematics of specific movements have been measured using IMUs; for example, the measurement of tibial acceleration during individual foot-strikes in runners [58], or the estimation of knee and hip joint angles during jump landings [59].

2.4 Training Load and Injury

The relationship between training load and injury has been at the forefront of sports medicine research in recent years [60]. This section will first review the conceptual relationship between load and musculoskeletal injury, followed by longitudinal research into the load-injury relationship in professional sport, and finally, common methodological issues within this field of research.

2.4.1 Injury Aetiology Models

In sports medicine literature, aetiological models have been proposed with the goal of outlining pathways by which athletic injuries occur, and facilitating research and applied interventions targeting injury prediction and prevention. Though it is beyond the scope of the work to comprehensively review the evolution of injury aetiology models, several models key to understanding the load-injury relationship will be discussed. Common amongst these models, either implicitly or explicitly, is the concept of load vs. capacity, whereby injury occurs when load exceeds capacity.

The balance of load and capacity was first evident in Ettema's stress-capacity model of human injury, describing an interaction between external and internal factors [61]. The stress component of this model is a product of the athlete's environment, whilst the capacity component is determined by internal factors. In van Dijk's update stress-strain-capacity

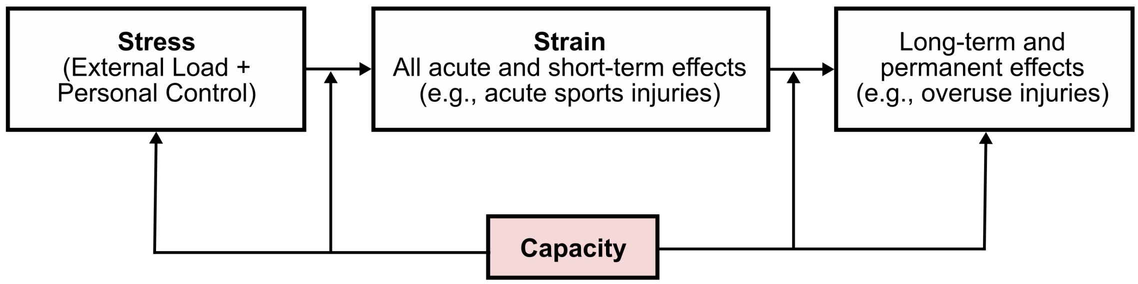


Figure 2.5: Stress-strain-capacity model. Redrawn from van Dijk et al. [62]

model [62] (Figure 2.5), a third component, strain, represents the response of an athlete to a bout of load; in this regard, the occurrence of injury is no longer simply a balance of two isolated parameters, but instead, it is a complex interaction of multiple factors over time. Importantly, the stress-strain-capacity model depicts the athlete as an active manipulator of the load experienced, and not simply a passive recipient. Furthermore, the model accounts for the recurrent nature of load, acknowledging the short and long-term psychophysiological effects of a bout of load.

More recently, aetiology models have focused on the multifactorial nature of athletic injury. Meeuwisse's [63] multifactorial model originates with an athlete who may or may not be predisposed to injury, determined by internal risk factors such as age, physical characteristics, and prior injury. Importantly though, internal risk factors alone are unlikely to result in injury. The action of external risk factors such as playing surface or weather may further increase the athlete's susceptibility to injury. Finally, an inciting event is necessary for injury to occur; for example, a ballet dancer may underrotate during a *double tour en l'air*, leading to a landing with excessive knee torsion, and consequently an anterior cruciate ligament tear. Whilst the landing may have been the inciting event, the athlete may have been susceptible due to factors such as previous knee injuries, lower body weakness, or a hard floor surface. Meeuwisse et al. [64] updated the multifactorial (Figure 2.6) to account for the recurrent nature of athletic activity; risk factors are not stationary, but instead shift as a result of repeated exposure, and the resulting adaptation or maladaptation.

Bittencourt et al. [65] proposed a paradigm shift from reductionism to complexity, arguing for movement away from isolated risk factors and instead towards interactive relationships—ultimately, injuries do not occur as a result of a single risk factor. The authors proposed a complex systems model, i.e., a model comprised of multiple parts that inconsistently and non-linearly interact with each other (Figure 2.7). Furthermore, these parts are altered, and new parts may emerge, as a result of their interaction. Thus, athletic injury is a result of a recursive and unpredictable interplay between multiple physiological,

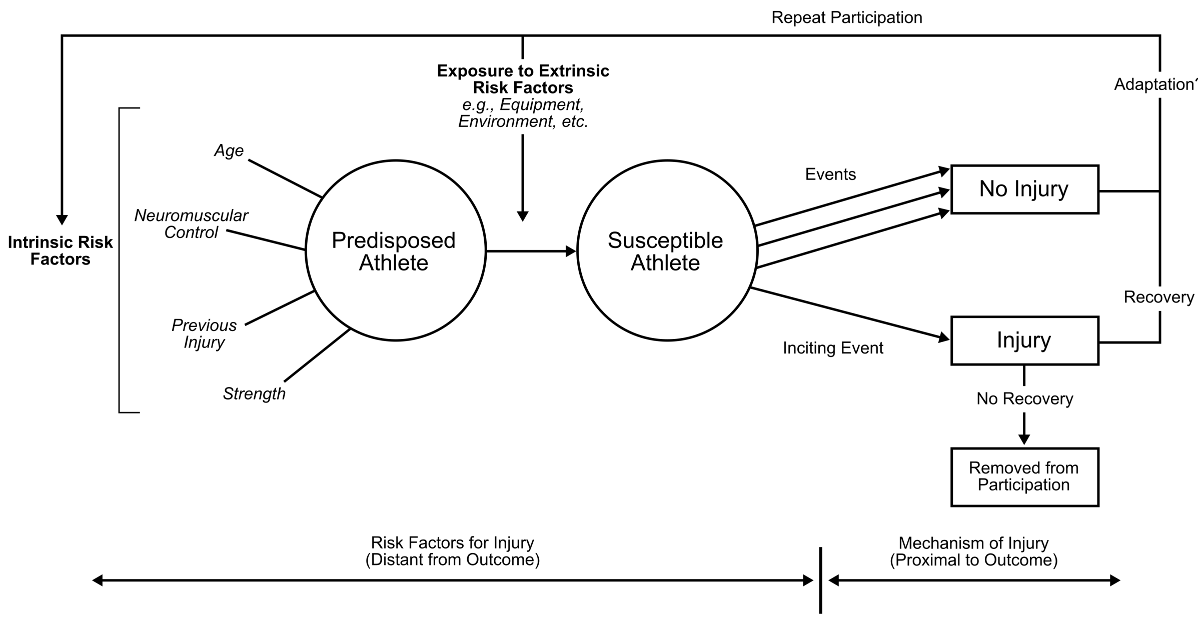


Figure 2.6: A dynamic, recursive model of etiology in sport injury. Redrawn from Meeuwisse et al. [64]

technical, environmental, and psychological factors.

The previously outlined models, whilst outlining an injury pathway, fail to describe an explicit chain of events, at a structural level, which detail the process by which injuries occur. McIntosh [66] devised a biomechanical model of sports injury, whereby injury is akin to structural failure of a physiological tissue, occurring as a result of energy transfer to the tissue. Importantly, McIntosh [66] identifies the mechanical properties of the tissue as determining the manner in which the body responds to the load. Injury prevention strategies must, therefore, target either a reduction in the load experienced by the tissue, or an increase in the tolerance of the tissue to that load.

2.4.1.1 A Materials Science Approach to the Load-Injury Relationship

In recent years, several etiological models have been devised with the intent of more explicitly defining a specific chain of causal events culminating in athletic injury. These pathways have built on McIntosh's model [66], adopting a materials science approach whereby musculoskeletal injury is a biomechanical event, occurring when physiological tissue reaches a point of material failure (i.e., fracture or deformation) [67]. In essence, whilst athletic injury is multifactorial, ultimately, these factors contribute to injury by affecting physiological tissue load or capacity, and thus influencing a mechanical fatigue pathway.

This approach is underpinned by the assumption that physiological tissue follows the

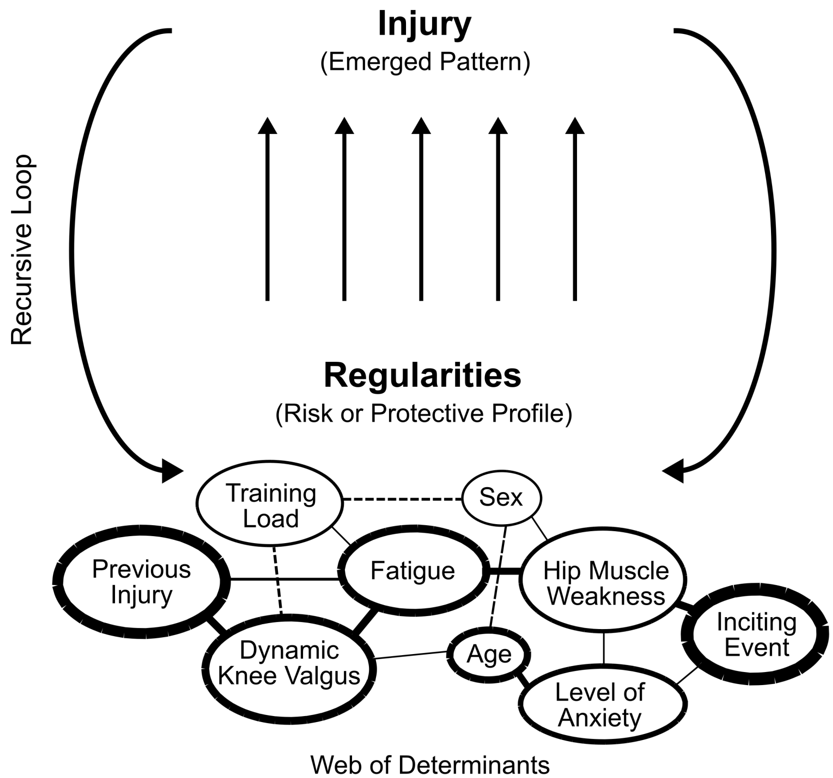


Figure 2.7: Complex model for sports injury. Redrawn from Bittencourt et al. [65]

same physical laws as any other material: when the stress and strain placed on a tissue exceed the strength of that tissue, material failure will occur [67]. At a tissue level, microstructural damage accumulates (i.e., mechanical fatigue) in response to repeated mechanical load [68]. The load-bearing properties of the tissue are often reduced following microstructural damage; the accumulation of this microdamage may result in material failure at mechanical loads below the material's monotonic strength [67]. In bone, this microdamage most commonly manifests as either linear microcracks—50–100 µm cracks resulting from repetitive loading—or diffuse damage—clusters of cracks which typically occur in tensile regions of bone due to creep (i.e., material deformation following repetitive mechanical stress) [69]. In tendon, microdamage takes the form of kinked fibres, or localized fibre dissociation and ruptures [67].

Microdamage, whilst providing the stimulus for remodelling and adaptation [68], may also be implicated in the development of macro-stress and material failure. A stress-life plot (Figure 2.8) describes the relationship between the magnitude of material stress and the number of cycles the material can endure before failure. This relationship can be described by an inverse power law:

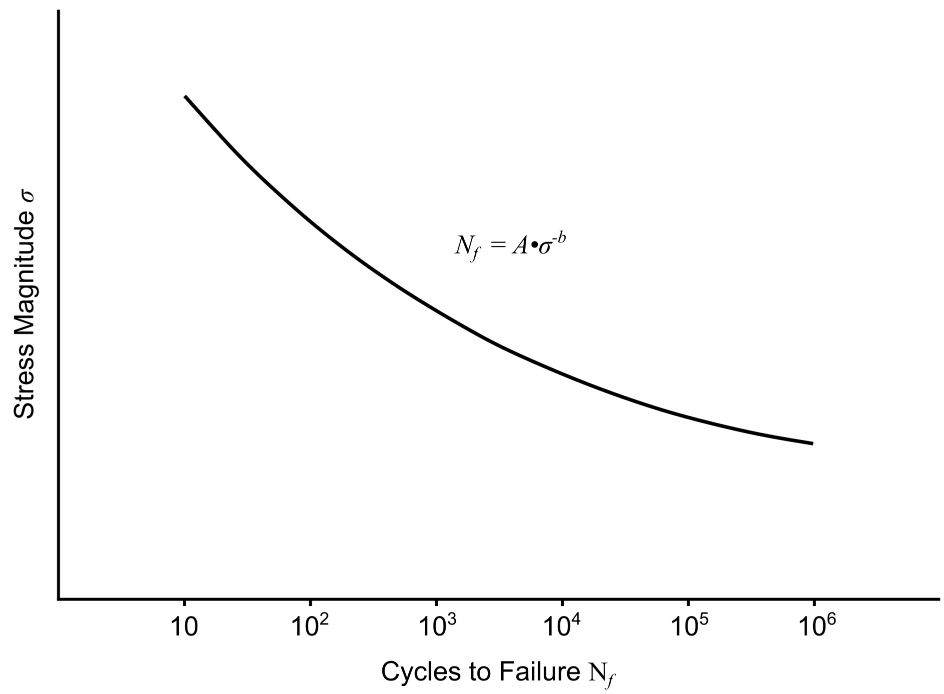


Figure 2.8: Theoretical stress-life plot, or S-N curve, for a material subjected to cyclic loading. Redrawn from Edwards et al. [67]

$$N_f = A \cdot \sigma^{-b}$$

where N_f is the number of cycles until failure, A is a proportionality constant, σ is the peak magnitude of the stress, and b is the slope of the curve. If this relationship does apply to overuse injuries in sport, then tissue damage would increase much more rapidly with tissue stress magnitude than with the number of loading cycles. Thus, cumulative tissue load does not equate to cumulative tissue damage; the damage incurred from one cycle at 2 σ, for example, would theoretically be greater than two cycles at 1 σ.

The framing of athletic injury as a mechanical fatigue phenomenon holds important implications for measurement of training load [67]. From a mechanical loading perspective, the aim of a load measurement tool is ultimately to estimate the forces experienced by a given physiological tissue (or a proxy of these forces), such that the damage to that tissue, and subsequently its risk of mechanical failure, can be quantified [20]. Researchers and practitioners should, therefore, first question the extent to which a load measurement tool is even a valid measure of the forces experienced by a physiological tissue. Secondly, should the tool be valid, is it suitably accurate to approximate tissue damage; given the exponential relationship between tissue load and tissue damage, the magnitude of any errors in this measurement are amplified. To illustrate this shortcoming, even the 3% errors in tibial force estimation calculated by Matijevich et al. [70] translate to an ~18% error in the measurement of bone damage; to the author's knowledge, no currently available wearable system offers field-measurement of tissue forces with error in the region of 3%.

Importantly, the risk of tissue failure is determined not solely by tissue load, but by the interplay between tissue load and tissue load capacity [71, 72]. To this end, Kalkhoven et al. [72] presented a detailed conceptual framework for stress-related, strain-related, and overuse injury, characterized by the relationship between these two factors (Figure 2.8). The athlete's physiology serves as the base of this model, composed of modifiable intrinsic physiological factors (e.g., muscle mass, tendon composition), non-modifiable intrinsic physiological factors (e.g., age, anatomy, injury history), and extrinsic factors contributing to physiology (e.g., training load, nutrition).

The model then diverges into two pathways, the first of which defines factors affecting tissue-specific strength. Tissue-specific strength is dictated by the relationship between the passive mechanical properties of the tissue, and the active regulation of the mechanical properties of the tissue. For tissue types that cannot actively alter their mechanical properties (i.e., bone, tendon), changes in tissue strength are determined by prior physiological adaptation. For example, bone mineral density, and tendon stiffness, elasticity, and cross-sectional area have been shown to increase following mechanical load. The mechanical properties of muscles and joints, on the other hand, can be actively regulated via muscle activation. Consequently, several injury risk factors may influence injury risk via altering muscle activation, e.g., fatigue, glycogen depletion.

The second pathway defines factors contributing the loads experienced by a given physiological tissue, whereby the stress and strain experienced is a product of two interrelated factors. Firstly, the forces experienced by that tissue, determined by the impact or force applied during the movement (e.g., ground reaction force), external factors affecting the tissue-specific loading (e.g., footwear, playing surface), and the athlete's physical characteristics which contribute to the loading of the tissue (e.g., neuromuscular control, strength). Secondly, the forces experienced by the tissue interacts with the tissue's mechanical properties to determine the stress and strain, illustrated in junction one of Figure 2.9. Importantly, some biological tissues have the ability toto alter their stiffness, and thus their material properties are not consistent.

The two pathways come together at junction two of Figure 2.9, representing the interplay of tissue-specific stress and strain and the strength of the tissue. The extent of the resulting damage determines the outcome of the bout of loading; whilst either acute or gradual onset injuries occur when the tissue-specific stress and strain exceeds the material

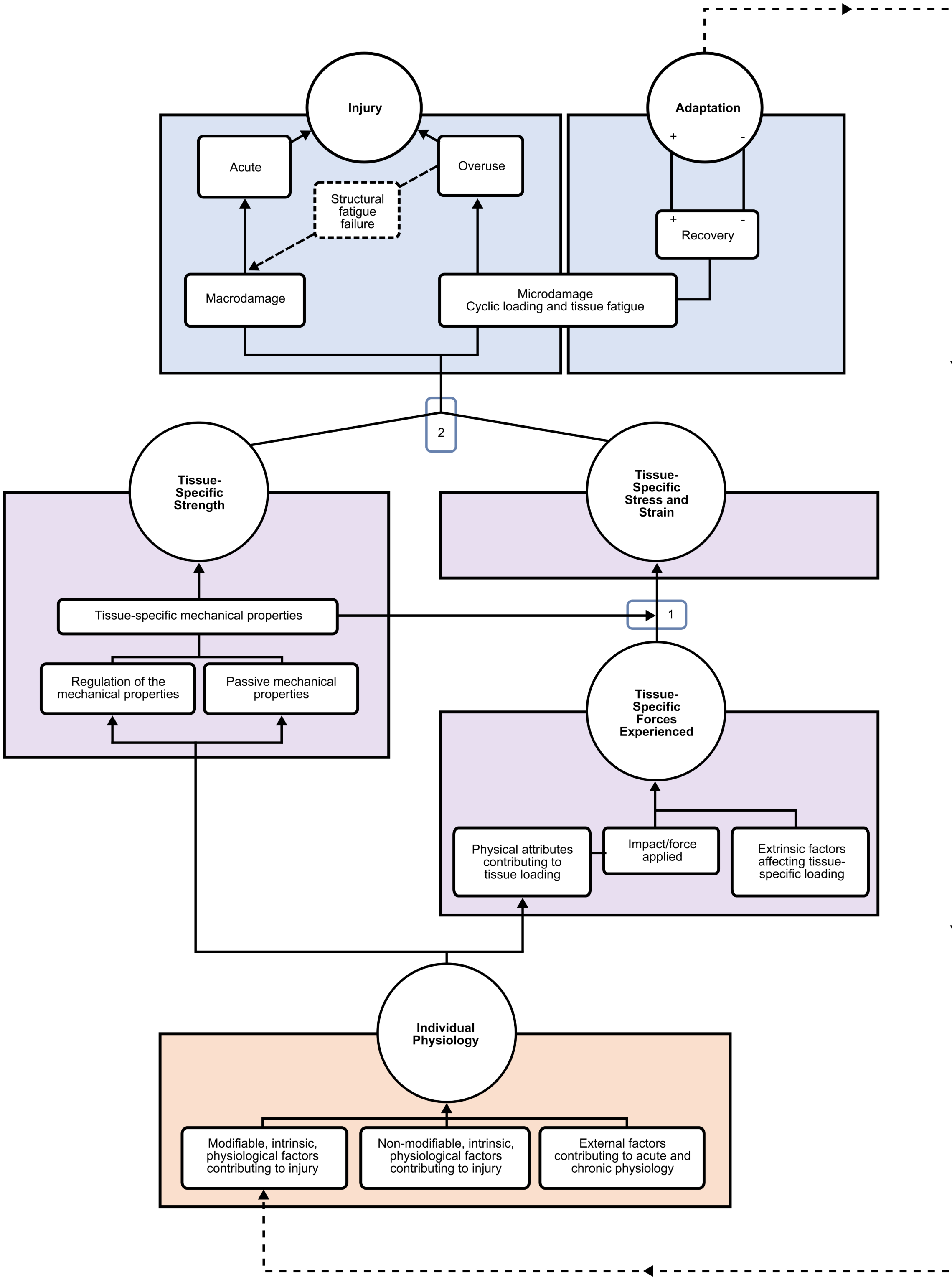


Figure 2.9: A detailed framework for stress-related, strain-related, and overuse injury. Redrawn from Kalkhoven et al. [72].

strength of that tissue, microdamage is an important stimulus for adaptation. The outcome of any given loading cycle, therefore, feed back into the individual's modifiable physiological factors for future loading bouts.

Sections 4.2–4.4 will address research studies that have investigated associations between training load and musculoskeletal injury. Sections 4.2 and 4.3 will provide brief overviews of the results of studies investigating absolute and relative training loads, respectively, whereas critical analysis of the flaws of these studies will be discussed more broadly in section 4.4 as many limitations are common amongst these studies.

2.4.2 Absolute Training Loads

A large body of research has investigated the relationships between the training load accumulated by an athlete or athletes in a fixed period and the subsequent risk of injury. Most commonly, this period of training load has been grouped by one or more weeks (i.e., one-week load [73, 74], two-week load [73], etc.), grouped by a single session (e.g., distance run in training [75], overs delivered in a match [43], pitches thrown in a match [42], etc.), or grouped by a season or pre-season (e.g., 12-month match exposure [76], pre-season session count [77]).

The first study investigating the relationship between training load and injury risk was that of Lyman et al. [42] in a sample of 298 youth baseball pitchers across two seasons. A J-shaped relationship was observed between the cumulative number of pitches thrown before a game, and the odds ratio for elbow pain during or following that game. Similar investigations into the load-injury relationship have since been conducted in sports such as cricket [78, 79], Australian football [80], association football [73, 81], rugby union [82], and rugby league [83], amongst others [84]. Whilst findings vary across studies and sports, two common themes have emerged from the literature:

- *Moderate to high chronic loads may have a protective effect against injury* [73, 85, 43]. Exposure to load may be an important stimulus for adaptation. As a result, those athletes who have not experienced a high prior load may possess underdeveloped physical qualities, and thus may be at a greater risk of injury. Chronic training loads have, therefore, been suggested to be synonymous to the athlete's fitness [86].

- *Very high loads may increase the risk of injury* [74, 87]. Exposure to excessive load can result in tissue microdamage and reductions in cognitive and neuromuscular performance, which may indirectly or directly result in injury. In this respect, some authors have suggested that acute loads are synonymous to fatigue [73].

The J-shaped relationship between training load and injury first identified by Lyman et al. [42] has, therefore, become well-established, underpinning many load-management principles and strategies existing in high-performance sport today.

2.4.3 Relative Training Loads

Load-injury research has commonly investigated relative training loads, either as an alternative to, or in addition to absolute training loads. In other words, researchers are interested not only in the magnitude of the accumulated load, but also how that load relates to a prior period of load. Theoretically, excessive progressions in training load are indicative of a level of physical stress for which the athlete is not prepared.

2.4.3.1 Week-to-Week Changes in Training Load

One of the most common measures of relative training load used is the week-to-week change in load experienced by an athlete. Large week-to-week changes in load have been associated with injury in professional rugby union [82], rugby league [16], association football [88], and Australian football [80, 89] players, and novice runners [90]. Further, an anecdotal '10% rule' is commonly referenced by non-academic websites or blogs, suggesting week-to-week increases in load should not exceed 10% [91, 92].

2.4.3.2 The Acute Chronic Workload Ratio

The acute:chronic workload ratio (ACWR) [85] is a method of monitoring the relationship between two components of training load: a recent period of load (acute load), suggested to represent the athlete's state of fatigue, and the training load accumulated over a longer period (chronic load), suggested to represent an athlete's fitness. To calculate the ACWR, the acute load is divided by the chronic load, such that a value greater than one represents a relative increase in load, whilst a value below one represents a relative decrease in load [85]. Acute:chronic workload ratios outside of a certain 'sweet spot' (typically 0.8–1.3) are suggested to be indicative of an increase in injury risk [17].

The ACWR is derived from Banister's systems model of human performance, whereby the interplay between fitness and fatigue has been extrapolated to athletic injury [93]. The ACWR was first presented in the scientific literature by Hulin et al. [78] under the name *training stress balance*. The internal (session-RPE) and external (total number of balls bowled) workloads of 28 fast bowlers were measured over five Australian domestic cricket seasons. Both internal and external ACWRs above 2 were associated with significant increases in injury risk in the following week. The ACWR has since been applied to numerous sports, using a multitude of training load variables, the results of which are mixed. Since its proposal, the ACWR has been widely adopted by science and medicine practitioners working in sport, but has also been the subject of considerable criticism and debate (see section 4.4).

One central theme has emerged from research into relative training loads and injury risk: *acute spikes in training load may be associated with an increased risk of injury* [17]. Current best practice regarding load-management for the mitigation of athletic injury risk can, therefore, be simplified into three broad rules of thumb [17]:

1. Athletes should avoid periods of very high acute or chronic training loads.
2. In-season, athletes should establish and maintain moderate-to-high chronic training loads.
3. Athletes should avoid rapid increases in training load.

2.4.4 Considerations for Longitudinal Load-Injury Research

A large body of recent research exploring the load-injury relationship has used a cohort design, in which a group of athletes are observed over one or more competitive seasons. Training load and injury data are recorded, following which statistical analyses are undertaken to determine associations between the two. Whilst this study design is not novel within epidemiological research, load-injury cohort studies became far more common following initial ACWR research [78]; many aspects of these studies have since been critiqued. This section will first explore overarching critiques common across this body of research, followed by those applying to specific articles.

2.4.4.1 Correlation and Causation

A common flaw of load-injury cohort studies is the overinterpretation of their results, whereby the authors erroneously suggest that due to a correlation between load and injury, this relationship is causal [94]. Examples of this overinterpretation are common:

> "sudden increases in workload, above which fast bowlers are accustomed, increase the likelihood of injury in the following 1-week period" [78]

> "Acute:chronic workloads of 1.00–1.25 offer protective effects for players. Therefore, medical and coaching staff should utilise this training load component as it has shown relationships with injury risk for elite soccer players" [81]

> "athletes should limit weekly increases of their training load to $< 10\%$, or maintain an acute:chronic load ratio within a range of 0.8–1.3, to stay in positive adaptation and thus reduce the risk of injuries" [17]

This assumption of a cause-effect relationship is invalid if the underlying intention, study design, and statistical analysis underpinning the research do not facilitate this outcome. This is particularly true for the load-injury relationship, for which a myriad of potentially confounding factors exists. As a result, the suggestion that alterations in load can meaningfully affect injury risk is yet unfounded, and recommendations to remove athletes from training or meet certain thresholds are unjustified [95].

2.4.4.2 Hypothesizing After the Results are Known

Kerr [96] presented the concept of *hypothesizing after the results are known* (HARKing), whereby researchers use their results to formulate a hypothesis which is presented as if it were *a priori*. There are multiple reasons for which a researcher may knowingly or unknowingly HARK, for example, to increase the chances of publication, because of hindsight bias, or to improve the narrative of the investigation. The field of load-injury research has previously been suggested to be at high-risk of HARKing [94]; this is perhaps a result of the dogma which has been established in several ACWR studies (i.e., the protective effect of high chronic training loads and the increase in injury risk following an acute spike in training load), and their conformity to a theoretical model that was embraced by science and medical practitioners in sport.

2.4.4.3 Statistical Power

Achieving a sample size to reliably determine load-injury associations is challenging for several reasons. Firstly, injury events are rare. As a result, researchers are required to collect hundreds of thousands of athlete exposure hours such that sufficient injury events will have occurred to reliably determine associations with risk factors [97]. Secondly, the multifactorial nature of athletic injury means that a host of known risk factors should be included in an analysis, and as a result, the number of required injury events increases to account for the additional covariates [97]. Finally, it has been suggested that because not all injuries share common mechanisms, it is invalid to analyse all injuries under the assumption that the load-injury relationship will be consistent across each injury type [20]. In other words, the load-injury relationship for one injury type may not be the same as the load-injury relationship for another injury type. As a result, the researcher should observe a sufficient number of each injury sub-group, and not simply consider all injuries to be comparable.

2.4.4.4 Conceptual Basis

Regardless of any associations which have been observed in load-injury studies, some academics have questioned the extent to which training load variables and injury are even conceptually related [20]. In other words, is there any valid causal pathway between commonly measured training load variables and a musculoskeletal injury? This argument stems from i) the fact that existing training load variables are inaccurate measures of physiological tissue load [70], ii) the non-linear relationship between tissue load and tissue damage, increasing the magnitude of these inaccuracies [67], and iii) the stochastic nature of tissue failure, making injury prediction uncertain even in the presence of a perfect measurement of tissue damage [67]. When discussing this critique, it is important to consider that even a weak relationship between a training load variable and tissue damage may reveal a meaningful relationship given sufficient sample size. However, whilst wearable data may, therefore, justify some broad strokes recommendations regarding training load manipulation (e.g., avoid large spikes in training load, progress training load gradually, etc.), the validity of manipulating training load to alter injury risk in individual cases is unjustified given the high degree of error [20].

2.4.4.5 Statistical Analysis

Load-injury study designs are complex, and often this complexity is not accounted for in the statistical analysis [98]. For example, data are commonly sourced from sports teams over multiple seasons, resulting in unbalanced repeated measures designs, and both time-varying and time-invariant variables. Furthermore, injury is multifactorial in nature, and thus a multitude of risk factors should be accounted for. Finally, the load-injury relationship may be confounded by a host of factors which may not be immediately apparent [65].

In a commentary on the use of longitudinal study designs in load-injury research, Windt et al. [98] outlined five challenges in the application of statistical modelling: inclusion of between-person and within-person effects; use of time-varying and time-invariant variables; violation of independency assumptions due to repeated measures on the same individuals; missing or unbalanced data; and the role of time. Of the 34 articles reviewed in the study, 22 used a regression (most commonly binary logistic regression) and 10 used a correlation. Furthermore, over half of the articles did not address the assumptions of the model, and 44% provided no justification for the use of their model.

2.4.4.6 Multiple Comparisons

Multiplicity issues arise due to an inflated rate of type 1 errors as a result of multiple testing [99]. For example, if a dataset is used to investigate the load-injury relationship, multiplicity issues may arise in three main cases. Firstly, when statistical tests are conducted to investigate the relationship between multiple independent variables (e.g., one-week load, two-week load, three-week load, etc.) and the dependent variable (injury); secondly, when statistical tests are conducted to investigate differences between multiple levels of an independent variable (e.g., moderate load vs. low load, moderate load vs. high load, moderate load vs. very high load); and thirdly, when statistical tests are conducted to investigate relationships between an independent variable (training load) and multiple dependent variables (e.g., multiple injury types) [99]. As more tests are conducted, the likelihood of encountering a type I error due to random sampling error increases [99]. When conducting multiple statistical tests, it is important that researchers either make adjustments for multiple comparisons, or acknowledge the implications of multiplicity for their results.

2.4.4.7 Confounding via schedule

Bornn et al. [100] presented a simulation study demonstrating a confounding effect of training schedule on the relationship between ACWR and injury risk. The authors used real-world association and American football data to simulate 1000 competitive seasons such that injury risk for each session was directly proportional to the PlayerLoad™ measured in that session. In doing this, injury data were simulated such that ACWR would have no influence on injury risk. Nonetheless, ACWRs below 0.8 and above 1.3 were predicted to result in 6.8% (association football) and 10.5% (American football) increases in injury risk. Whilst this example is specific to the ACWR (because the current session load is included in the acute load), training schedule may feasibly confound the load-injury relationship in other cases. For example, the load undertaken in any given session may be related to prior training scheduling, and thus injury may be related to that prior training via the current session load.

2.4.4.8 Confounding via Exposure

It is both logical and evidenced that the chance of sustaining an injury increases with exposure (e.g., if someone train for more time, all else equal, there is more chance they will be injured). Kalkhoven et al. [20] highlight that not only is the above true, but a positive relationship also exists between exposure time and cumulative load. Load-injury associations may, therefore, result simply from a failure to account for exposure time, i.e., it is unsurprising that a high load may be associated with injury given that in order to achieve a high load the athlete is likely to have been exposed to training or competition for a greater duration. When attempting to identify relationships between load and injury, researchers must, therefore, account for the duration for which the athlete is 'at risk'.

2.4.4.9 Unnecessary discretization

The transformation of a continuous variable into a number of discrete categories is common in load-injury research [101]. For example, a continuous cumulative load variable may be converted into *low*, *moderate*, or *high* load categories; or a group of individuals may be divided into *weak* and *strong* groups based on a continuous measure of lower-limb strength. This approach results in a loss of information, as any intra-category variation is lost. In the case of dividing athletes by strength, for example, an athlete at the 50th percentile is considered to be at the same risk of injury as an athlete at the 99th percentile). Discretization of a continuous variable may also result in an increase in the false discovery rate, as each category is typically compared to a reference category, without accounting for the increase in statistical comparisons. Finally, Wainer et al. [102] demonstrated that the binning of a continuous variable can result in the appearance of a trend that does not truly exist. Instead, the use of polynomials or splines has been recommended where non-linear trends may exist in continuous data [103].

2.4.4.10 Scaling of a ratio

Ratios are typically used to control for a denominator that shares a relationship with the numerator [104]. If this relationship exists, then it should hold true that no relationship will exist between the ratio and the denominator. Conversely, when no relationship exists between the numerator and the denominator, a relationship between the ratio and the denominator will be constructed artificially. In the context of the ACWR, Lolli et al. [105] used data from professional association football players to demonstrate the absence of a relationship between uncoupled acute and chronic training loads, and subsequently an unwanted negative relationship between the ACWR and the chronic training load. Thus, the conversion of acute and chronic training loads into an inappropriate ratio may, in fact, simply add noise to the data.

2.4.4.11 Mathematical coupling

Lolli et al. [106] identified that the use of an ACWR in which the acute period is included in the chronic period (e.g., where the acute period is days -1 to -7, and the chronic period is days -1 to -28) results in spurious correlation between the acute and chronic values. In other words, correlation will be evident despite there being no physiological association between the two parameters. This mathematical coupling affects the ACWR itself, and thus any relationship between coupled ACWRs and injury risk may not be grounded in any physiological process.

2.4.4.12 Summary

It is evident from critiques of existing training load research that recent approaches to load-injury research have failed to adequately address the methodological issues that arise in longitudinal epidemiological research. Though it is likely—and perhaps unavoidable—that applied research in this field will have methodological limitations, researchers should make a serious attempt to address these pitfalls where possible. In many cases, and particularly those relating to decisions around the analysis of data, these limitations are avoidable.

2.5 Training Load in Dance

In recent years there has been a large increase in the number of research articles investigating the quantification and implications of training load in sport. Whilst this interest in training load is increasingly present in the world of dance [107, 108]—and a modest increase in training load research in dance is evident—the training loads experienced by dancers, and methods for the quantification of that training load, remain comparatively unexplored. Nonetheless, non-balletic genres of dance likely represent the closest comparison to the training loads undertaken in ballet, and as such, warrant discussion. This section will first discuss research into methodological approaches to the quantification of load in dance, followed by qualitative and quantitative research into the load-injury relationship in dance. Descriptive studies into the training load demands of professional ballet are excluded from this section due to their inclusion in Chapter 3.

2.5.1 Research into Methods of Quantifying Training Load in Dance

2.5.1.1 Session-RPE

Three studies have investigated the validity of s-RPE in dance. In a cohort of pre-professional contemporary dancers, Jeffries et al. [109] observed mean individual correlation coefficients of 0.72 and 0.77 for relationships between s-RPE and e-TRIMP, and s-RPE and b-TRIMP, respectively. Correlations were weaker, however, during ballet class compared with both contemporary class and rehearsals. Similarly, in pre-professional contemporary dancers, Surgenor and Wyon [110] observed a correlation coefficient of 0.72 between s-RPE and e-TRIMP, though it should be noted that the analyses failed to account for the repeated measures within individuals. Like the results of Jeffries et al. [109] weaker relationships were observed during ballet class compared with contemporary class and rehearsals. Whilst the authors suggest this may reflect factors such as the differences in movement demands between genres, or environmental factors, it may simply reflect a range restriction bought about by the lack of variation observed between ballet classes (this possibility is discussed further in Chapter 6). Unlike both Jeffries et al. [109] and Surgenor and Wyon [110], in a cohort of elite adolescent ballet dancers Volkova et al. [111] observed no significant relationships between s-RPE and either e-TRIMP or b-TRIMP during a variety of dance classes. Differences in results between these studies may reflect the relatively young age of the cohort observed by Volkova et al. [111] (12–17 years of age). However, several methodological differences exist, for example, the measurement of resting HR, statistical analysis, and timepoint of data collection post-session.

2.5.1.2 Inertial Measurement Units and Accelerometers

Three methodological papers have explored the use of wearable technology as a means of quantifying external training load in dance. Almonroeder et al. [112] secured accelerometers to the superior iliac spine of their participants, observing very strong positive correlations between peak vertical acceleration and peak vertical ground reaction force (r = 0.95–0.98, $p < .001$), and between peak vertical ground reaction force and peak loading rates (r = 0.80–0.88, $p < .001$) across a series of *changement de pied* to exhaustion. It should be noted, however, that the mean values from a series of jumps were analysed (e.g., mean peak acceleration from the final 10 jumps), and not the relationships between peak values measured during single jumps. It is possible that this approach artificially inflated the strength of the relationship, as inaccuracies in individual jumps may have been averaged out across multiple jumps.

Hendry et al. [113] used accelerometer data and machine learning methods (support vector machines and artificial neural networks) to estimate continuous ground reaction forces during a series of unilateral and bilateral ballet jumps. Whilst root-mean-square-error values were low for entire ground reaction force profiles, relatively large error was observed in the estimation of peak forces. In the context of quantifying lower-limb load this may be particularly important given that small differences in tissue load may translate to large differences in tissue damage [67]. In a separate study, Hendry et al. [114] investigated the use of convolutional neural networks to identify balletic jumps and leg lifts. The algorithms were highly accurate in the identification of simple movement types (i.e., jump or leg lift) without the inclusion of transition movements ($> 97.3\%$). Less accurate identification was observed, however, with the addition of transition movements (80.6–84.0%), and the requirement to classify movements more precisely (56.5–74.9%). For simplistic classifications, single sensor algorithms performed similarly to multi-sensor algorithms, though for more complex classifications multi-sensor algorithms were required.

Finally, one research group investigated the use of accelerometers to quantify the biomechanical demands of the dance aerobic fitness test [115]. Triaxial accelerometers were secured to the cervical spine and the distal aspect of the lower limb in 26 university dancers. Progressive increases in both cervical spine and lower limb PlayerLoad™ were observed across the five stages of the test, leading the authors to conclude that triaxial accelerometry is a valid measure of the biomechanical demands of dance. It is important to note though, that no criterion measure of biomechanical load was used, and the dance aerobic fitness test is validated against oxygen uptake [116]. Furthermore, the authors suggest that distal lower-limb accelerometry is a more valid measure of training load than cervical accelerometry; this suggestion is not based on any data collected in the study, and is contrary to the suggestions of other research groups [117].

2.5.2 Load-Injury Research in Dance

2.5.2.1 Qualitative Research

Several research groups have conducted qualitative investigations into injury and/or training load in dance. Bowling [118] surveyed 188 UK-based professional dancers (139 classical, 49 modern) on their chronic and recent injury history. Of the dancers who had sustained an injury in the previous six months, 38% cited feelings of being overtired, overworked, and run down as the cause of injury, whilst 12% cited the demands of difficult choreography, and 7% cited the continual repetition of difficult movements during rehearsals. Furthermore, 29% of all respondents suggested less pressure and overwork as an injury prevention strategy. Similarly, in a national enquiry into dancers' health and injury [119], 57% of ballet professionals perceived fatigue/overwork to be a cause of injury (the highest cited cause), whilst 38% stated that repetitive movements were a contributing factor.

Bolling et al. [12] conducted focus groups with professional ballet dancers and staff of the Dutch National Ballet, identifying key themes relating to ballet injuries, injury risk factors, and injury prevention strategies. Both staff and dancers identified excessive workloads, and the imbalance between load and load capacity, as the primary reasons for injury occurrence. Participants specifically identified the inconsistency of loading across the calendar, and the limited recovery time the schedule permits, as load-related factors contributing to injury. Regarding the concept of load capacity, dancers suggested that the limited prior knowledge of the roles for which they must prepare made it challenging to prepare physically; this is compounded by the difficulty dancers face preparing for a role whilst concurrently experiencing high rehearsal workloads.

Unlike the previously mentioned studies, a sample of vocational dance students did not deem the workloads associated with their educational course to be excessive [120]; dancers did, however, allude to a culture of overtraining. Some dancers believed that this culture may have been designed to prepare students for the demands of a professional career, though most dancers suggested that following the transition from pre-professional to professional dance workloads decreased.

Whilst the qualitative research into the load-injury relationship in dance is relatively sparse, it is consistent in its allusion to high workloads. Evidently, both dancers and artistic staff believe that these workloads are implicated in injury, and there is scope for improvements in the scheduling of rehearsal and performance schedules.

2.5.2.2 Quantitative Research

Jeffries et al. [121] collected s-RPE and injury data across a single season in a professional contemporary dance company (n = 7 men and 9 women). The mean weekly s-RPE was 6685 ± 1605 AU (range 464–10391 AU). Dancers' RPEs were higher during performances than rehearsals (8.0 ± 1.4 AU vs. 5.2 ± 1.9 AU), however, performances were shorter in duration (84.9 ± 34.1 min vs. 109 ± 34.1 min). Whilst the sample size was insufficient to reliably determine any associations between load and injury, the authors did observe the highest injury rates when dancers completed their highest training loads (individualised upper 33% of weeks).

Boeding et al. [122] investigated the relationships between s-RPE and symptoms of overuse injury (Self-Estimated Functional Inability because of Pain questionnaire) across a seven-week training period in 21 dancers (11 men, 10 women). Mean weekly training loads were between 2540–4761 AU, across a mean of 14.4 dance events per week. The greatest number of rehearsal exposures was observed in weeks with the least number of performance exposures. A mixed-effects model revealed no significant associations between s-RPE and symptoms of overuse injury; however, a t-test indicated that weekly training loads were significantly greater in symptomatic dancers.

Finally, Cahalan et al. [123] investigated relationships between dance exposure, measures of wellbeing, and self-reported injury in collegiate Irish (n = 21) and contemporary dancers (n = 29). Mean weekly dance exposure was 12.2 ± 3.2 and 7.6 ± 2.4 $h \cdot week^{-1}$

for contemporary and Irish dancers, respectively. Wilcoxon signed rank tests were used to investigate relationships between injury events and dance exposure. In weeks preceding an injury event, contemporary dancers reported higher dance exposure compared with the four previous weeks, though no such finding was observed in Irish dancers.

When considering these investigations, it is important to note that many of the methodological issues discussed in section 2.4.4 are common. Most notably, the use of inappropriate statistical tests (e.g., correlational analyses), small sample sizes, non-standard injury definitions, and a failure to account for known confounders. It is, therefore, reasonable to suggest that until further high-quality load-injury research in dance is published, best practices for load management in dance should instead be extrapolated from sporting research.

2.6 Thesis Structure and Chapter Aims

This thesis is organised into three sections (Figure 2.9), dividing the chapters into three broad research themes detailed below. For each experimental chapter, a specific research question is detailed at the start of each paragraph.

2.6.1 Thesis Section 1

The first section of this thesis—Chapters 2 and 3—reviews current research into training load in sport, training load in dance, and the activity demands of ballet.

2.6.1.1 Chapter 2: The Quantification and Implications of Training Load in Sport and Dance: A Literature Review

In this chapter, a critical review of current research relevant to this thesis was presented. Given the sparsity of research investigating training load in dance, much of this chapter focused on research from the field of sports medicine. The review began with an overview of high-level concepts relating to training load and the training process, before discussing common methods for the quantification of training load. The chapter then went on to examine literature concerning the relationship between training load and injury. Finally, research into methods of training load quantification in dance, and the load-injury relationship in dance was reviewed.

2.6.1.2 Chapter 3: The Activity Demands and Physiological Responses Observed in Professional Ballet: A Systematic Review

What are the physical demands undertaken by professional ballet dancers?

This chapter presents a systematic review of literature investigating the activity demands or physiological responses observed in professional ballet. Four subject areas are included in this review: i) session-specific activity demands of ballet, ii) general activity demands of ballet (i.e., not limited to a single session), iii) immediate physiological responses to ballet, and iv) delayed physiological responses to ballet. Unlike the previous chapter, this review was limited to studies concerning only professional ballet dancers, and not broader genres of dance. Twenty-two relevant research articles are identified, the methods and results of which are synthesized and reviewed.

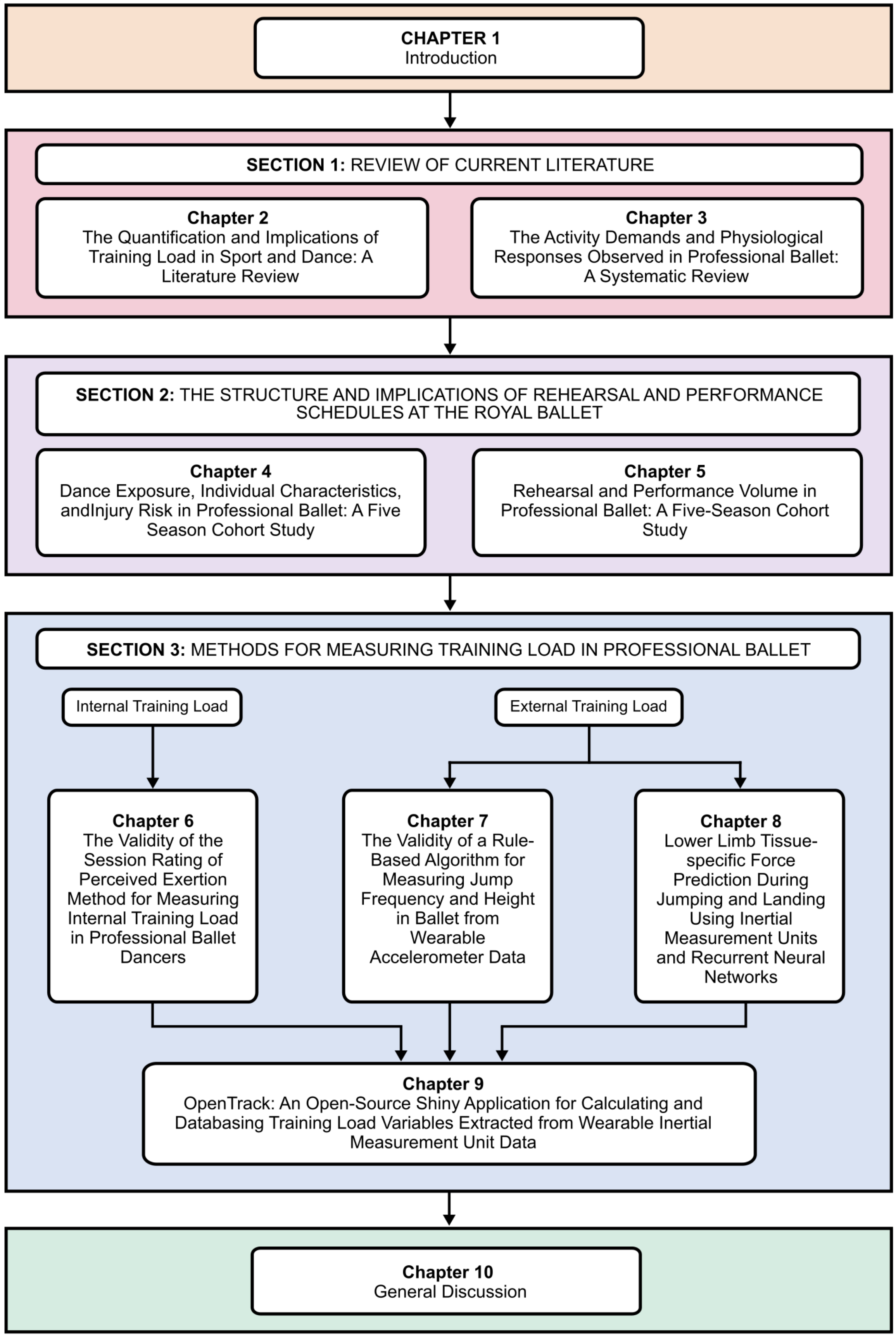


Figure 2.10: Schematic illustrating the structure of the thesis.

2.6.2 Thesis Section 2

The second section of this thesis—Chapters 4 and 5—contains an exploration and analysis of five seasons of scheduling and injury data at The Royal Ballet.

2.6.2.1 Chapter 4: Dance Exposure, Individual Characteristics, and Injury Risk over Five Seasons in a Professional Ballet Company

What relationships exist between patterns of rehearsal and performance exposure, and the risk of musculoskeletal injury?

This chapter investigates the relationships between dance exposure variables (7-day accumulated exposure, 28-day accumulated exposure, week-to-week change in exposure), individual characteristics (age, sex, company rank, injury history), and musculoskeletal injury rates (overuse medical attention injuries, overuse time-loss injuries, traumatic medical attention injuries, traumatic time-loss injuries). Hazard ratios for each injury type and independent variable are extracted from cox proportional hazards and shared frailty models, accounting for repeated measures across individuals, and controlling for exposure time. The practical implications of the results for load management in professional ballet are discussed.

2.6.2.2 Chapter 5: The Structure of a Professional Ballet Season: A Longitudinal Analysis of Scheduling Demands Across Five Years

How are rehearsals and performances scheduled, and how can these schedules be manipulated and optimised?

This chapter contains an in-depth analysis of the scheduling practices and seasonal structure at The Royal Ballet. The study focuses on providing data and practical recommendations with which load management strategies—as recommended in Chapter 4—can be implemented. Firstly, a descriptive analysis of the rehearsal and performance volume imposed by a professional ballet schedule is conducted, with a focus on the variation within and between sexes, company ranks, and timepoints in the season. Secondly, differences in the durations of rehearsal dancers completed in preparation for various ballets are investigated, as are the factors associated with these differences.

2.6.3 Thesis Section 3

The third section of this thesis—Chapters 6 to 9—contains the development and validation of several practical methods for the quantification of training load in ballet, and an open-source application with which healthcare practitioners working in ballet can manage the training load of dancers.

2.6.3.1 Chapter 6: The Validity of the Session Rating of Perceived Exertion Method for Measuring Internal Training Load in Professional Ballet Dancers

Is session-RPE a valid measure of internal training load in professional ballet?

This chapter investigates the validity of s-RPE as a measure of internal training load in professional ballet dancers. Dancers are observed across a total of 79 ballet classes and 139 rehearsals during which s-RPE and continuous HR are measured. Reference measures of internal load are b-TRIMP and e-TRIMP. Individual and repeated measures correlations for the relationships between s-RPE and each reference measure are calculated to investigate the validity of s-RPE.

2.6.3.2 Chapter 7: The Validity of an Open-Source Rule-Based Algorithm for Measuring Jump Frequency and Height in Ballet using Wearable Accelerometer Data

Can IMUs be used to quantify jump load in professional ballet?

This chapter investigates the validity of a rule-based algorithm to calculate jump load from wearable accelerometer data. Firstly, the accuracy of the algorithm's jump event identification is investigated during ballet class, using time-motion analysis as a reference measure. Secondly, the accuracy of the algorithm's jump height estimation for *sautés*, *jetés*, and double tours is investigated using a force plate as the reference measure.

2.6.3.3 Chapter 8: Lower Limb Tissue-specific Force Prediction During Jumping and Landing Using Inertial Measurement Units and Recurrent Neural Networks

Can IMUs be used to quantify lower-limb tissue forces during jumping movements for use outside of a laboratory?

This chapter presents the development and evaluation of a recurrent neural network which estimates lower-limb physiological tissue forces from IMU data. Participants wearing five IMUs completed 18 sets of jumping movements on a force plate whilst motion capture data are recorded. Musculoskeletal modelling is conducted using the FreeBody lower-limb model to calculate Achilles and patellar tendon forces. Recurrent neural networks, with IMU variables as features and FreeBody forces as targets, are trained and evaluated using a leave-one-subject-out cross validation.

2.6.3.4 Chapter 9: OpenTrack: An Open-Source Shiny Application for Calculating and Databasing Training Load Variables Extracted from Wearable Inertial Measurement Unit Data

This chapter presents an open-source software platform that healthcare practitioners working in ballet can use to analyse and database training load data. For most ballet companies at present, it is unlikely that healthcare teams will have the financial power to invest in state-of-the-art wearable technology systems. This app contains a user interface to the algorithms detailed in chapters 7 and 8, functionality to input s-RPE data, and several dashboards to visualize these internal and external training load variables.

2.6.4 General Discussion

This chapter concludes the thesis, bringing together the key findings from each chapter. Initially, a high-level summary of each chapter is provided, following which the findings are discussed in reference to the state of play regarding the use of training load management in professional ballet companies. The chapter concludes with best practice recommendations for healthcare practitioners, and recommendations for future research.

CHAPTER 3

The Activity Demands and Physiological Responses Observed in Professional Ballet: A Systematic Review

3.1 Abstract

Aim: The aim of this study was to systematically review research into the activity demands and physiological responses observed in professional ballet. **Methods:** PubMed, Web of Science, SPORTDiscus, and ProQuest were searched for original research published prior to January 2021 relating to 1) the session-specific activity demands of professional ballet, 2) the general activity demands of professional ballet, 3) the immediate physiological responses to professional ballet, or 4) the delayed physiological responses to professional ballet. From an initial 7672 studies, 22 met the inclusion criteria. Methodological quality was assessed using the Mixed Methods Appraisal Tool and a modified Downs and Black Index. **Results:** Professional ballet is intermittent; however, activity characteristics and intensity vary by session type and company rank. Performances involve high volumes of jumps (5.0 ± 4.9 jumps·min^{-1}), *pliés* (11.7 ± 8.4 *pliés*·min^{-1}), and lifts (men - 1.9 ± 3.3 lifts·min^{-1}), which may result in near-maximal metabolic responses. Ballet classes are less metabolically intense than performance during both barre and centre (< 50% maximal oxygen uptake). Neither the activity demands nor the physiological responses encountered during rehearsals have been investigated. Day-to-day activity demands are characterized by high volumes of rehearsal and performance (> 5 h·day^{-1}), but half is spent at intensities below 3 METs. Evidence is mixed regarding the delayed physiological responses to professional ballet, however, metabolic and musculoskeletal adaptations are unlikely to occur from ballet alone. The mean Downs and Black score was 62%. Appraisal tools revealed that a lack of clarity regarding sampling procedures, no power calculation, and a poor quality of statistical analysis were common limitations of the included studies. **Conclusions:**

Given the large working durations and high rates of jumps, *pliés*, and lifts, managing training loads and recovery may be a focus for strategies seeking to optimize dancer health and wellbeing. Ballet companies should provide dancers with opportunities and resources to engage in supplementary physical training. Future research should explore the demands of rehearsals and the longitudinal training loads experienced by professional ballet dancers.

3.2 Introduction

Historically, ballet dancers have been perceived solely as performing artists, for whom principles such as artistry, musicality, and grace are paramount [**?**]. Increasingly, however, the importance of physical qualities such as strength, power, and endurance are being recognised, and ballet professionals are considered artistic athletes [7], facing comparable physical demands to elite sportspeople [6]. Ballet has been compared to aesthetic sports such as gymnastics [6], with which it shares classically based movement sequences and extreme ranges of motion. The activity profile of ballet performance, however, appears to be similar to sports such as tennis [124] or basketball [44]; ballet is intermittent, involving bouts of high intensity movement, as well as lower intensity periods during which dancers may be acting or off-stage [125].

Injury incidence in professional ballet (4.4 time-loss injuries per 1000 h [15]) is comparable to that observed in sports such as cricket match-play (1.9–3.9 injuries·1000 h^{-1} [126]) and association football training (4.1 injuries·1000 h^{-1} [127]). As a result, there have been calls for ballet companies to adopt more robust approaches to science and medical provision [128]. The periodization of workload [108], implementation of screening protocols [129], increase in strength and conditioning provision [6], and introduction of specialized healthcare services [130] have been proposed as potential methods of mitigating injury risk. The development of science and medicine provision in professional ballet, however, requires a thorough understanding of the physical demands of the activity. A systematic review is, therefore, needed to synthesize research into the physical demands of professional ballet, making the evidence accessible to those working in the field, and providing guidance for future research.

The purpose of this systematic review was, therefore, to identify, evaluate, and summarize research on the activity demands and physiological responses observed during professional ballet, and provide recommendations to direct future investigations.

3.3 Methods

3.3.1 Design and Search Strategy

The systematic review was conducted in accordance with the Preferred Reporting Items of Systematic Reviews and Meta-analyses statement [131]. A systematic search of the electronic databases SPORTDiscus, Web of Science, ProQuest, and PubMed (MEDLINE) was performed on 7th January 2021 for scientific literature published prior to that date. The following Boolean phrase was used to search each database: (Ballet* OR Ballerin* OR dancer OR dancing) AND (demand* OR response OR responses OR intensity OR volume OR load OR physical OR cardiovascular OR metabolic OR workload OR physiologic* OR schedule OR jump* OR lift* OR *pointe* OR flexib* OR mobility OR strength OR power OR muscul* OR endurance) NOT Title (collegiate OR elderly OR older OR obesity OR cancer OR disease OR "cerebral palsy" OR education). Results from Web of Science and ProQuest were further filtered to include relevant subject areas only; a full list of excluded subject areas can be found in Appendix D. Hand-searches of each included study's reference list and the reference list of a review paper pertinent to the topic [6] were completed to identify further relevant articles.

3.3.2 Inclusion and Exclusion criteria

Searches and screening processes were independently conducted by two reviewers. Reviewers exported all article details into a Microsoft Office Excel spreadsheet, wherein duplicate results were automatically removed. The remaining articles were manually screened in Excel; titles were first screened for relevance, followed by abstracts and full texts where necessary. Four reviewers met, and discrepancies in included articles were resolved by consensus.

Studies were included in the review if they met the following inclusion criteria: (1) Participants were professional ballet dancers; (2) During the study, participants either completed a prescribed ballet session or followed their normal ballet schedule; (3) Data were reported on the activity demands or physiological responses encountered; and (4) The study was written in English. Activity demands were defined as any data pertaining to the volume and/or movement intensity of activity completed by the participant(s). Activity demands were further divided into two subsections: (1) *Session-specific activity demands* - the activity taking place within a specific session (e.g., the number of jumps completed in a ballet class); or (2) *General activity demands* - activity characteristics not limited to a single session (e.g., the number of jumps completed during a week). Physiological responses were divided into two subsections: (1) *Immediate physiological responses* – those recorded on the same day as the activity; and (2) *Delayed physiological responses* – those recorded on a different day to the activity. To be included, delayed physiological responses must have reported a physiological measurement both pre- and post-ballet activity; studies which measured a physiological characteristic at a single time point were not included. All relevant study designs were included in the review.

Studies were excluded if (1) data were reported on a mixed group of dancers (e.g., ballet and contemporary dancers, professional and non-professional ballet dancers), and data for a professional ballet subgroup could not be extracted, (2) no methodology was provided for variables of interest, (3) data were only reported on injured dancers, or (4) only contractual hours were used as a measure of dance exposure. Review articles, and data pertaining to hormonal responses related to professional ballet were not included in this review. The latter data were excluded to limit the scope of the review.

3.3.3 Data Extraction and Analysis

Data were extracted from each study by the lead reviewer. For each study, publication details (author, year, journal) and demographic data (age, height, weight, sex) were extracted. Methodological details (sample size, participant characteristics, session type, study duration, phase of season, equipment, protocol, measurements), and results (descriptive data regarding activity demands and/or physiological responses, results of statistical analyses) were recorded. Data displayed in figures were extracted using WebPlotDigitizer v.4.3 [132]. Where further details were required, authors of the study were contacted for clarification. Given the heterogeneity in subject areas and variables reported, a meta-analysis was not conducted.

3.3.4 Assessment of Methodological Quality

Due to the heterogeneity of study designs used, included studies were evaluated using the Mixed Methods Appraisal Tool (version 2018; MMAT [133]). A modified version of the Downs and Black checklist for the assessment of methodological quality [134] was used to identify more specific strengths and weaknesses of included studies. For each of the criteria, a single point was available (*yes* – 1, *no* – 0, *unable to determine* – 0), except question five, for which two points were available. Question 27 was adjusted to read: "Was a power analysis conducted, and if so, did the sample size provide sufficient statistical power to detect an effect?". Downs and Black scores were interpreted using the following thresholds: $\leq 50\%$ - *Poor*, 50–70% - *Fair*, 70–90% - *Good*, $> 90\%$ - *Excellent* [135]. Risk of bias was assessed at a study level (i.e., individual outcomes within a study were not assessed seperately). No articles were excluded based on their methodological quality.

3.4 Results

3.4.1 Search Results

The hand-search and search of electronic databases yielded an initial 7672 results of which 1258 were duplicates. Following title and abstract review, 6293 articles were excluded. Full texts of the remaining 121 articles were screened, of which 99 did not meet the inclusion criteria. Twenty-two studies were, therefore, included in the review. A comprehensive search and selection flow diagram is presented in Figure 3.1.

3.4.2 Study Characteristics

Detailed characteristics of each included study can be found in Table 3.1. Five studies investigated session-specific activity characteristics of professional ballet (class: $n = 2$ [4, 136], performance: $n = 3$ [46, 125, 137]); ten studies investigated the general activity characteristics involved in professional ballet [5, 14, 15, 138, 139, 140, 141, 142, 143, 144], four studies investigated the immediate physiological responses to professional ballet (class: $n = 2$ [4, 136], rehearsal: $n = 1$ [4], performance: $n = 3$ [4, 125, 145]); eight studies investigated the delayed physiological responses to professional ballet [7, 140, 143, 146, 147, 148, 149, 150]. Five studies used entirely female cohorts, and 17 studies used mixed cohorts.

3.4.3 Quality Assessment

The mean Downs and Black score was 62%. Five studies were classified as *poor* [4, 125, 136, 137, 145], twelve studies were classified as *fair* [5, 7, 46, 138, 139, 142, 140, 146, 147, 148, 149, 150], five studies were classified as *good* [14, 15, 141, 143, 144], and no studies were classified as *excellent*. Full results of the MMAT and the modified Downs and Black assessments can be found in Tables 3.2 and 3.3, respectively. All studies presented a clear research question, and collected data allowing them to address the question. Articles were most commonly marked down due to a failure to sufficiently explain sampling procedures.

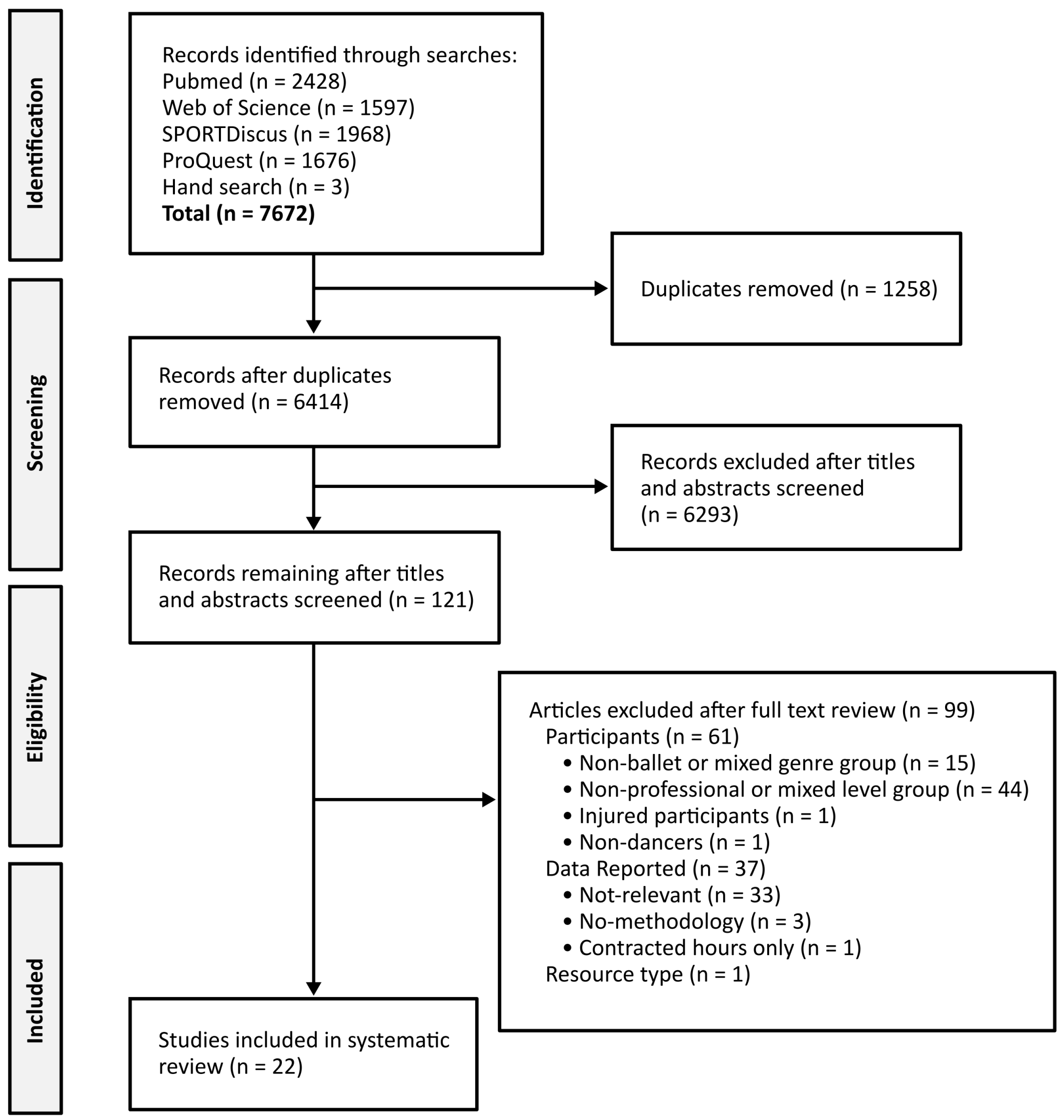


Figure 3.1: Flow diagram of the systematic search process.

Table 3.1: Characteristics of studies included in the systematic review.

Study	Design	Participant Characteristics					Activity Demands		Phys. Responses		Common
		n	Age (y)	Height (m)	Mass (kg)	BMI (kg/m²)	Session	General	Immediate	Delayed	Data
Wyon et al. [46]	CS	24 M	-	-	-	-	•				1
		24 F	-	-	-	-					
Twitchett et al. [137]	CS	24 M	-	-	-	-	•				1
		24 F	-	-	-	-					
Schantz & Åstrand [4]	CS	6 M	28 ± 6	1.80 ± 0.04	70.0 ± 4.0	-	•		•		
		7 F	25 ± 8	1.66 ± 0.55	52.0 ± 5.0	-					
Cohen et al. [136]	CS	7 M	24	1.78	68	-	•		•		
		8 F		1.66	49.5	-					
Cohen et al. [125]	CS	6 M	25 ± 3	1.76 ± 0.03	63.9 ± 1.5	-	•		•		
		7 F	24 ± 4	1.66 ± 0.03	48.9 ± 3.9	-					
Seliger et al. [145]	CS	3 M	31 ± 8	1.81 ± 0.06	72.3 ± 6.7	-			•		
		3 F	35 ± 12	1.64 ± 0.05	53.3 ± 4.1	-					
Costa et al. [138]	RD	22 M	34 ± 7	-	-	23.6 ± 1.1		•			
		31 F	34 ± 6	-	-	19.5 ± 1.1					
Twitchett et al. [142]	CS	51 F	28 ± 5	1.61 ± 0.03	46.1 ± 4.5	-		•			
Kozai et al. [141]	CS	25 M	26 ± 5	1.78 ± 0.04	70.7 ± 5.6	22.3 ± 1.3		•			
		23 F	27 ± 5	1.63 ± 0.04	49.5 ± 4.9	18.5 ± 1.4					
Allen et al. [15]	Incidence	25 M	23 ± 5	1.80 ± 0.04	71.7 ± 4.7	22.2 ± 1.4		•			
		27 F	25 ± 6	1.62 ± 0.04	49.2 ± 4.0	18.9 ± 1.6					
Allen et al. [14]	Pre-post	27 M[A]	24 ± 4	1.79 ± 0.04	71.7 ± 5.5	-		•			
		28 F[A]	25 ± 5	1.63 ± 0.03	49.9 ± 4.6	-					
Wyon et al. [143]	CS	21 M	-	1.81 ± 0.04	69.5 ± 5.6	21.3 ± 1.4		•			2
		21 F	-	1.66 ± 0.03	50.9 ± 4.5	18.5 ± 1.4					

Table 3.1 (cont.)

Study	Design	Participant Characteristics					Activity Demands		Phys. Responses		Common Data
		n	Age (y)	Height (m)	Mass (kg)	BMI (kg/m²)	Session	General	Immediate	Delayed	
Wyon et al. [144]	CS	21 M	-	1.81 ± 0.04	69.5 ± 5.6	21.3 ± 1.4		•			2
		21 F	-	1.66 ± 0.03	50.9 ± 4.5	18.5 ± 1.4					
Cohen et al. [5]	CS	15 M	24 ± 4	1.77 ± 0.05	66.5 ± 4.8	-		•			
		15 F	23 ± 4	1.65 ± 0.04	49.6 ± 3.9	-					
Doyle-Lucas et al. [139]	CS	15 F	24 ± 1	-	-	18.9 ± 0.2		•			
				-	-						
Kim et al. [140]	Pre-post	43 F	26 ± 3	1.64 ± 0.04	49.4 ± 4.4	18.4 ± 1.0		•		•	
Wyon et al. [150]	NRCT	2 M	28 ± 0	1.79 ± 0.02	66.5 ± 0.4	-				•	
		5 F	27 ± 5	1.64 ± 0.02	50.7 ± 6.5	-					
Koutedakis & Sharp [7]	RCT	22 F	25 ± 1	-	45.0 ± 4.5	-				•	
Koutedakis et al. [147]	Pre-post	17 F	27 ± 1	1.60 ± 0.06	-	-				•	
Kirkendall et al. [146]	Pre-post	14 M	25 ± 3	1.78 ± 0.06	67.2 ± 8.3	-				•	
		14 F	24 ± 4	1.67 ± 0.07	53.9 ± 6.1	-					
Micheli et al. [148]	Pre-post	29 M	24 ± 6	-	71.6 ± 6.4	-				•	
		39 F	22 ± 4	-	51.6 ± 4.6	-					
Ramel et al. [149]	RCT	6 M	24 (19-47)	-	-	-				•	
		4 F		-	-	-					

CS, Cross-sectional; RD, Retrospective descriptive; RCT, Randomised controlled trial; NRCT, Non-randomised controlled trial; BMI, Body mass index; M, Male; F, Female. Common data indicates that the same data were used in multiple studies.

Table 3.2: Results of the Mixed Methods Appraisal Tool assessment of methodological quality.

Study	Screening[A]		Criteria[B]				
	1	2	1	2	3	4	5
Quantitative descriptive							
Wyon et al. [46]	Y	Y	?	?	Y	N	Y
Twitchett et al. [137]	Y	Y	?	?	Y	N	Y
Schantz & Åstrand [4]	Y	Y	?	?	Y	Y	N
Cohen et al. [136]	Y	Y	?	?	Y	N	Y
Cohen et al. [125]	Y	Y	?	?	Y	N	?
Seliger et al. [145]	Y	Y	?	?	Y	N	N
Costa et al. [138]	Y	Y	Y	?	N	Y	Y
Twitchett et al. [142]	Y	Y	?	?	Y	N	Y
Kozai et al. [141]	Y	Y	Y	Y	Y	N	N
Allen et al. [15]	Y	Y	Y	Y	Y	N	Y
Wyon et al. [143]	Y	Y	?	?	Y	N	Y
Wyon et al. [144]	Y	Y	Y	Y	Y	N	Y
Cohen et al. [5]	Y	Y	?	?	Y	N	Y
Doyle-Lucas et al. [139]	Y	Y	?	?	Y	N	N
Non-randomized							
Allen et al. [14]	Y	Y	Y	N	Y	N	Y
Kim et al. [140]	Y	Y	?	Y	Y	N	Y
Wyon et al. [150]	Y	Y	?	Y	Y	N	Y
Koutedakis et al. [147]	Y	Y	?	Y	N	Y	Y
Kirkendall et al. [146]	Y	Y	?	Y	Y	N	Y
Micheli et al. [148]	Y	Y	Y	Y	Y	Y	Y
Randomized controlled trials							
Ramel et al. [149]	Y	Y	Y	?	Y	N	Y
Koutedakis & Sharp [151]	Y	Y	Y	Y	?	N	?

Y, Yes; N, No; ?, Unable to determine.
A Screening questions: 1) Are there clear research questions?; 1) Do the data address the research questions?
B Quantitative descriptive criteria: 1) Was the sampling strategy relevant?; 2) Is the sample representative of the target population?; 3) Were measurements appropriate?; 4) Is the risk of nonresponse bias low?; 5) Is the statistical analysis appropriate?
Non-randomized criteria: 1) Are participants representative of the target population?; 2) Are measurements appropriate regarding both the outcome and intervention (or exposure)?; 3) Are there complete outcome data?; 4) Are confounders accounted for in the design and analysis?; 5) Is the intervention administered (or exposure occurred) as intended?
Randomized controlled trial criteria: 1) Is randomization appropriately performed?; 2) Are groups comparable at baseline?; 3) Are there complete outcome data?; 4) Are outcome assessors blinded?; 5) Did participants adhere to the intervention?

Table 3.3: Results of the Downs and Black assessment of methodological quality.

Study	Reporting									Ext. Validity			Bias							Confounding						Power	Score	Criteria	Pct.	Rating
	1	2	3	4	5	6	7	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27				
Costa et al. [138]	1	1	1	1	1	1	0	-	1	1	0	1	-	-	1	-	1	-	0	1	0	-	-	0	-	0	12	19	63%	Fair
Schantz & Åstrand [4]	1	1	1	0	1	1	0	-	0	0	0	1	-	-	1	-	0	-	1	-	0	-	-	0	-	0	8	18	44%	Poor
Cohen et al. [136]	1	1	1	1	1	1	1	-	0	0	0	1	-	-	0	-	0	-	1	-	0	-	-	0	-	0	9	18	50%	Poor
Kozai et al. [141]	1	1	1	1	2	1	1	0	1	1	1	1	-	-	1	-	0	-	1	-	0	-	-	1	1	1	17	20	85%	Good
Cohen et al. [125]	1	1	1	1	1	0	0	-	0	0	0	1	-	-	-	-	0	-	1	-	0	-	-	0	-	0	7	17	41%	Poor
Doyle-Lucas et al. [139]	1	1	1	1	1	1	1	-	0	0	0	1	-	-	1	-	0	-	0	-	0	-	-	0	-	1	10	18	56%	Fair
Twitchett et al. [137]	1	1	0	0	1	1	0	-	0	0	0	1	-	-	1	-	1	-	0	-	0	-	-	1	-	0	8	18	44%	Poor
Wyon et al. [46]	1	1	0	0	1	1	1	-	0	0	0	1	-	-	1	-	1	-	1	-	0	-	-	1	-	0	10	18	56%	Fair
Micheli et al. [148]	1	1	0	1	1	1	1	0	1	1	0	1	-	-	1	1	0	-	1	-	0	-	-	0	1	0	13	21	62%	Fair
Kirkendall et al. [146]	1	1	0	1	1	1	1	0	0	0	0	1	-	-	1	1	1	-	1	-	1	-	-	0	0	0	12	21	57%	Fair
Twitchett et al. [142]	1	1	1	1	2	1	0	-	0	0	0	1	-	-	1	-	1	-	1	-	1	-	-	1	0	0	13	19	68%	Fair
Wyon et al. [144]	1	1	1	1	2	1	1	-	0	1	1	1	-	-	1	-	1	-	1	-	1	-	-	1	-	0	16	18	89%	Good
Allen et al. [14]	1	1	1	0	1	1	1	-	1	1	1	1	-	-	1	1	1	0	1	-	1	-	-	0	0	0	15	21	71%	Good

Table 3.3 cont.

Study	Reporting									Ext. Validity			Bias							Confounding						Power	Score	Criteria	Pct.	Rating
	1	2	3	4	5	6	7	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27				
Seliger et al. [145]	1	1	1	0	1	1	1	-	0	0	0	1	-	-	-	-	0	-	1	-	0	-	-	0	-	0	8	17	47%	Poor
Allen et al. [15]	1	1	1	1	2	1	1	0	0	1	1	1	-	-	1	1	1	-	1	-	1	-	-	1	1	0	18	21	86%	Good
Kim et al. [140]	1	1	1	0	1	1	1	0	1	0	0	1	-	-	1	1	1	1	1	-	1	-	-	0	1	0	15	22	68%	Fair
Koutedakis et al. [147]	1	1	0	1	1	1	1	0	0	0	0	1	-	-	1	0	1	1	1	-	1	-	-	0	0	0	12	22	55%	Fair
Ramel et al. [149]	1	1	0	1	1	1	0	0	1	1	1	1	0	0	1	1	0	0	1	1	1	1	0	0	0	0	15	27	56%	Fair
Koutedakis & Sharp [7]	1	1	0	1	1	1	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	1	0	0	1	0	16	27	59%	Fair
Wyon et al. [150]	1	1	1	1	1	1	1	1	1	1	0	1	0	0	1	1	1	0	1	1	1	0	0	0	1	0	18	27	67%	Fair
Wyon et al. [143]	1	1	0	1	2	1	1	-	0	1	1	1	-	-	1	-	1	-	1	-	1	-	-	1	-	0	15	18	83%	Good
Cohen et al. [5]	1	1	1	1	1	1	1	-	0	0	0	1	-	-	1	-	1	-	1	0	0	-	-	0	-	0	11	19	58%	Fair
Mean	1	1	0.6	0.7	1.2	1	0.7	0.2	0.3	0.4	0.3	1	0	0	1	0.9	0.6	0.5	0.9	0.8	0.5	0.7	0	0.3	0.5	0.1	12.7	19.4	62%	

Ext. Validity, External Validity.

Downs and Black criteria: 1) Clearly described hypothesis; 2) Main outcomes clearly described; 3) Participant characteristics described; 4) Interventions clearly described; 5) Distributions of principal confounders described; 6) Main findings clearly described; 7) Estimates of random variability given; 9) Characteristics of patients lost to follow-up described; 10) Actual probability values reported; 11) Subjects asked to participate were representative of the entire population; 12) Subjects who participated were representative of the entire population; 13) Facilities and equipment were representative of normal practice; 14) Subjects blinded; 15) Investigators blinded; 16) Any data dredging was made clear; 17) Analyses adjusted for follow-up lengths; 18) Statistical tests were appropriate; 19) Compliance with the intervention was reliable; 20) Main outcome measures were valid and reliable; 21) Intervention and control groups recruited from the same population; 22) Subjects were recruited over the same period of time; 23) Subjects randomized to intervention groups; 24) Randomization concealed from subjects and investigators; 25) Adequate adjustment for confounding factors; 26) Losses of patients to follow-up taken into account; 27) A power analysis was conducted, and sufficient power was achieved.

3.4.4 Session-Specific Activity Demands

3.4.4.1 Class

Two studies investigated the activity characteristics of ballet class [4, 136]. Schantz and Åstrand [4] report class durations of 60 min (30 min effective exercise time), made up of seven barre exercises (28 min, 10 s rest intervals), and five centre-floor exercises (32 min, 2-3 min rest intervals). Cohen et al. [136] report class durations of 75 minutes; movement sequences during barre, centre-floor, and *allegro* phases were 65 s, 35 s, and 15 s, and rest periods were 30 s, 85 s, and 75 s, respectively.

3.4.4.2 Rehearsal

No studies reported data on the activity characteristics of rehearsals.

3.4.4.3 Performance

Three studies investigated the activity characteristics of ballet performance [46, 125, 137]. During 5 roles from *Swan Lake*, *Giselle*, and *Études*, the acts/sections observed varied in duration from 14–43 min, with actual dance times ranging from 2–12.5 min (14–30% of performance) [125]. During successive variations, work-to-rest ratios of between 1:1.6 and 1:3.4 were observed [125]. Across 48 classical roles [46, 137], over half of the performance time was found to be spent at resting intensities (i.e. still or off-stage), and around a quarter at moderate or hard intensities. Male and female dancers performed jumps (5.0 ± 4.9 jumps·min^{-1}) and *pliés* (11.7 ± 8.4 *pliés*·min^{-1}) at similar rates, though males were involved in lifting their partners (1.9 ± 3.3 lifts·min^{-1}), whilst females were not [46, 137].

3.4.5 General Activity Characteristics

Ten studies reported data on the general activity demands undertaken by professional ballet dancers [5, 14, 15, 138, 139, 140, 141, 142, 143, 144]; activity demands were the primary outcome of only 2 of these studies [141, 142]. The results of studies reporting durations of physical activity, dance exposure, and supplementary training are presented in Figure 3.2.

Two studies investigated rest periods throughout the working day, reporting mean greatest rest breaks of 36 ± 31 min [142] and 35 ± 27 min [141]. One study describes daily self-reported energy expenditure of female dancers, which in two separate 7-day periods, was 3,571 ± 466 kcal and 3,154 ± 466 [140]. Two studies of the same company reported data relating to workload beyond the demands of a single week [14, 15]. The company performed between 142 and 145 shows per year, spanning between 15 and 20 productions

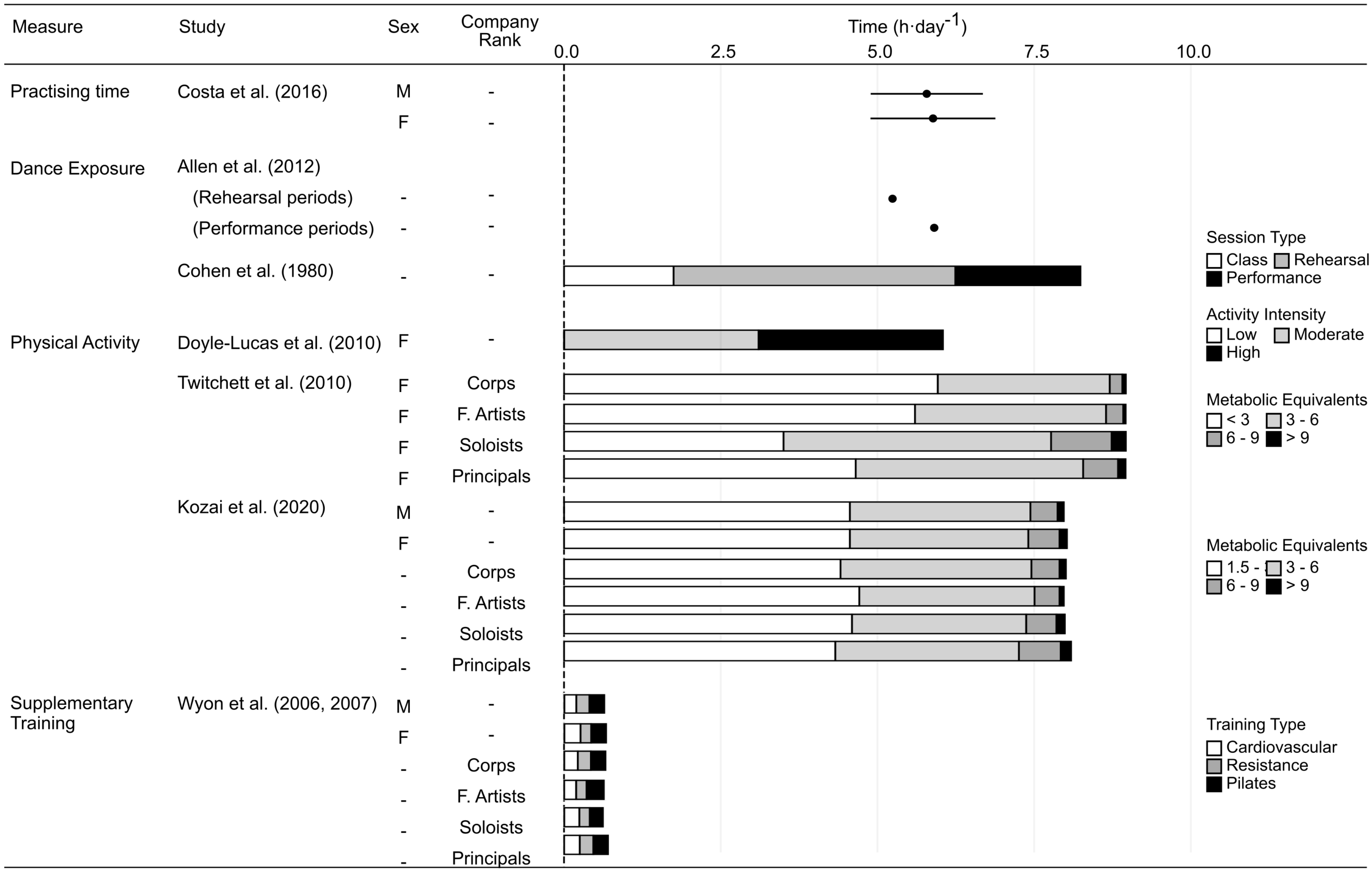


Figure 3.2: Overviews of studies reporting durations of physical activity, class, rehearsal, performance, or training undertaken by professional ballet dancers. Exposure reported in hours per week is converted to daily exposure assuming a 6-day week. F.Artists – First Artists; M – Male; F – Female.

per year [14]. The first of those seasons was 46 weeks long, consisting of 26 rehearsal weeks and 20 performance weeks [15]. Performance periods were 2–6 weeks in length, during which the company averaged 7 performances per week. The summer break was 5 weeks, and there was a 1-week break at mid-season.

3.4.6 Immediate Physiological Responses to Professional Ballet

3.4.6.1 Ballet Class

Two studies investigated the acute physiological responses to ballet class [4, 136]. Mean heart rate (66 vs 76% maximum) [136], oxygen uptake ($\dot{V}O_2$; 38 vs 49% $\dot{V}O_{2max}$ [136]; 36% vs. 45% $\dot{V}O_{2max}$ [4]), and energy expenditure (4.7 vs. 6.3 kcal·min^{-1}) [136] were greater during centre-floor exercises than barre exercises. Little change in blood lactate concentration ([BLa]) was seen between barre, centre-floor, and *allegro* phases of class (2.8 vs. 2.8 vs. 3.1 mmol·L^{-1}, respectively) [4].

3.4.6.2 Rehearsal

One research group [4] investigated the acute physiological responses to (non-performance) choreographed variations or *pas de deux*. Mean $\dot{V}O_2$ was 80 ± 7% of $\dot{V}O_{2max}$ (69-92% of $\dot{V}O_{2max}$), whilst mean post-activity [BLa] was 9.9 ± 3.1 mmol·L^{-1} (6.2-15.2 mmol·L^{-1}).

3.4.6.3 Performance

Three studies investigated the physiological responses to professional ballet performances [4, 125, 145]. Mean heart rates during performance were 134 [145] and 169 bpm (87% maximum) [125], and mean peak heart rates were 177 [145] and 184 beats·min^{-1} (94% maximum) [125]. One study [4] simply states that heart rates during performance were frequently close to maximum, peak [BLa] were similar to those observed following maximal cycling (~11 mmol·L^{-1}), and mean post-performance $\dot{V}O_2$ for two dancers was 85% of $\dot{V}O_{2max}$. One research group [145] reported an increase in both systolic (131 to 172 mmHg) and diastolic (73 to 96 mmHg) blood pressure from pre- to post-performance.

Table 3.4: Overviews of studies reporting data on the delayed physiological responses to professional ballet.

Measure	Study	Methods	Timepoints	Results
Body composition	Koutedakis & Sharp [151]	Body mass; skinfold thickness (4 sites); thigh circumference.	(1) Mid-January. (2) + 12 weeks.	No significant differences.
	Kirkendall et al. [146]	Hydrostatic weighing.	(1) Pre-season (August). (2) December.	No significant differences.
	Micheli et al. [148]	Body mass; skinfold thickness (7 sites).	(1) Preseason (August). (2) Postseason (May).	In females, body mass (51.6 ± 4.6 kg to 50.4 ± 4.5 kg, $p < .001$) and BF% (12.8 ± 2.7% to 11.5 ± 2.1%, $p < .001$) decreased. No significant differences seen in males.
	Kim et al. [140]	Body mass; bioelectrical impedence.	(1) 7 days pre-, and (2) 7 days post a 3-day performance period.	Significant increases were seen in BMI (+ 0.12 $kg \cdot m^2$, $p = .032$), LBM (+ 0.5 kg, $p = .002$), and TBW (+ 0.2 L, $p = .021$), but not in body mass or BF%.
	Koutedakis et al. [147]	Skinfold thickness (4 sites).	(1) Post-season. (2) Pre-season. (3) + 2-3 months.	No significant differences.
Lower-body strength/power	Koutedakis & Sharp [151]	Isokinetic knee flexion and extension.	(1) Mid-January. (2) + 12 weeks.	No significant differences.
	Kirkendall et al. [146]	Isokinetic knee flexion and extension.	(1) August. (2) December.	Significant differences in torque only observed at $180° \cdot sec^{-}1$ (males + 12%, females + 16%). For males and females, respectively, relative quadriceps torque increased by 3 and 6% for the right leg, and by 9 and 7% for the left leg.

Table 3.4 (cont.)

Measure	Study	Methods	Timepoints	Results
	Koutedakis et al. [147]	Isokinetic knee flexion and extension; Peak Wingate power.	(1) Post-season. (2) Pre-season. (3) + 2-3 months	Knee extension and flexion torques, and peak Wingate power all increased following the summer break.
	Wyon et al. [150]	Isometric knee extension; vertical jump height.	(1) January. (2) May.	No significant differences.
Aerobic Capacity	Koutedakis et al. [147]	Maximal incremental treadmill test (gas analysis).	(1) Post-season. (2) Pre-season. (3) + 2-3 months.	$\dot{V}O_{2max}$ (mL·kg·min^{-1}) increased following the summer break (41.2 ± 8.5 to 45.2 ± 7.1), and again following preseason (48.4 ± 6.8).
	Ramel et al.[149]	Maximal incremental cycle test (gas analysis, blood lactate concentration).	(1) Preseason. (2) + 10 weeks.	No significant differences in $\dot{V}O_{2max}$, [BLa], workload at 4 mmol·L^{-1}, or maximum workload.
Anaerobic Capacity	Koutedakis et al. [147]	Wingate mean power.	(1) Post-season. (2). Pre-season. (3) + 2-3 months.	No significant differences.
Flexibility	Koutedakis et al. [147]	Hamstring, trunk, and shoulder flexibility.	(1) Post-season. (2) Pre-season. (3) + 2-3 months.	Hamstring (208 to 226 deg), trunk (86 to 99 deg), and shoulder (40 to 61 deg) flexibility all increased following the summer break.

BF%, Body fat percentage; [BLa], Blood lactate concentration; $\dot{V}O_{2max}$, Maximum rate of oxygen consumption; TBW, Total body water.

3.4.7 Delayed Physiological Responses to Professional Ballet

Delayed physiological responses to professional ballet have been reported in 7 studies [7, 140, 146, 147, 148, 149, 150], the results of these studies are presented in Table 3.4. In 4 studies [140, 146, 147, 148], the primary aim was to investigate a response to ballet, whilst in 3 studies [7, 149, 150], the primary aim was to investigate the effect of an intervention (vitamin D supplementation [150], strength training [7], and cardiovascular training [149]), and consequently data for this review were taken from control groups.

3.5 Discussion

This is the first systematic review to synthesize research exploring the activity demands and physiological responses observed in professional ballet. A total of 22 articles were identified, spanning the subcategories of immediate and delayed physiological responses, and session-specific and general activity demands. We aimed to provide a summary to inform current practice in professional ballet companies, as well as identify gaps in the current body of literature, providing direction to researchers working within this field.

3.5.1 Session-Specific Physical Demands of Professional Ballet

Ballet is an intermittent activity, though the intensity of that activity varies by session-type. High intensity activity takes place during the latter phases of ballet class [136], however, the short duration of these bouts and the large inter-exercise rest periods limit the metabolic intensity of the session [4, 136]. Ballet performance is of a greater metabolic intensity; bouts of dancing are longer in duration [125] and are higher in both average and peak intensity [4, 125, 145]. However, studies investigating ballet performance have not randomly sampled productions or roles, and one research group [4] explicitly states that only moderately strenuous to very strenuous roles were analysed. Therefore, it appears that current research on the immediate physiological responses to ballet performance is representative of more physically demanding roles. In contrast, video analyses of 48 roles across classical repertoire [46, 137] suggest that most of a performance is spent at rest, particularly in the case of non-principal dancers. Only two studies reported the physical demands of specific performance roles [4, 125]; greater granularity in this regard may benefit science and medicine staff when preparing dancers for a specific role.

During performance [46, 137], dancers jump at a greater rate than that observed during volleyball [152] or basketball match-play [153]. Whilst average values (5.0 ± 4.9 jumps·min^{-1}) alone are high [46], it is evident from the standard deviation that there is large variation between roles. Recent research in sport has emphasized the importance of preparing athletes for the worst-case-scenarios they may encounter; neither study [46, 137], however, reports the maximum rate of jumping observed. The most physically demanding segments are likely to exceed the values reported [46]. A recent editorial highlighted jump load as an important injury analytic [154]. To this end, almost a quarter of injuries in one professional ballet company have been attributed to jumping movements [15]. The volume and biomechanics of jumping in professional ballet may, therefore, be important directions for future research, and are potential targets of injury prevention interventions.

No studies were identified investigating the activity demands taking place in rehearsals, and only one study [4] reported data on the immediate physiological responses to rehearsals. Although near-maximal intensity responses were observed [4], the 'rehearsals' were sessions in which dancers completed solo variations or *pas de deux* from classical repertoire, and not rehearsals as they might occur *in situ*. Subsequently, these responses may not be directly comparable to rehearsals, during which dancers may be learning choreography, practicing shorter segments, or stopping frequently to receive technical guidance. The physical demands of rehearsals, therefore, remain almost entirely unexplored within scientific literature, and no definitive conclusions can be made. This is particularly notable for two reasons; firstly, unlike classes—which follow a consistent structure—and performances—which are strictly choreographed—rehearsals are inherently more variable from day-to-day; secondly, rehearsal makes up most of a dancer's activity [5]. Further research is, therefore, required to elucidate the demands of ballet rehearsals, enabling science and medicine practitioners to better prepare dancers for their day-to-day demands, and understand the training loads they undertake.

3.5.2 General Activity Demands of Professional Ballet

Overtraining syndrome and overuse injuries are common in professional ballet dancers—to this end, ballet dancers themselves have suggested the imbalance between load and load-capacity is the underlying cause of injury [12]. Durations of dance exposure reported in included studies vary, though most studies support the notion that dancers complete over 5 h of dance activity per day [5, 14, 15, 138, 139, 141, 142]. To our knowledge, no published research exists demonstrating comparable training and performance exposure times in any other athletic population [152, 155, 156]. However, whilst scheduled dance time and self-reported activity is high [5, 15, 138], accelerometry studies suggest that much of a dancer's day may be spent at intensities below 3 METs [141, 142]. Additionally, these studies revealed that activity profiles vary by company rank. Future research should, therefore, avoid the use of company-wide exposure hours, and applied science and medicine practitioners should adopt individualized approaches to load management [5, 14, 15, 139].

Despite the recent influx of studies publishing data on the longitudinal workloads of athletes within sporting organizations, little research has explored longitudinal workloads in professional ballet. Although two studies [141, 142] conducted longitudinal activity monitoring, data are only reported pertaining to the demands of an average day. Furthermore, as data collection periods were only one [141] and three [142] weeks, reported values may not account for changes in activity which may occur as the repertoire changes across the course of a season. Although the count of shows performed by a professional touring company each season (142–145 shows, 15–20 productions) has been reported on two occasions [14, 15], it is not stated in how many of these shows individual dancers were involved. Further research is warranted exploring the longitudinal training load demands faced by professional ballet dancers.

Longitudinal activity monitoring in professional ballet may be facilitated by the use of wearable technology. Several studies have been published exploring and/or validating the use of wearable technology in professional ballet [112, 113, 114]; however, the application of these devices and algorithms is not yet evident. Ballet companies may face financial barriers to the implementation of wearable technology, however, methods such as session rating of perceived exertion [157] may provide a cost-effective alternative. Whilst cultural barriers to the implementation of load monitoring in dance may also exist, research in other dance genres [121], and at a non-professional level [158], suggests load monitoring may be of value.

3.5.3 Delayed Physiological Responses to Professional Ballet

It has previously been suggested that participation in ballet alone is insufficient to elicit meaningful physiological adaptation [7, 144]; included studies reported mixed results in this regard. Increases in lower limb strength [146, 147] and aerobic capacity [147] have been demonstrated following a ballet preseason, though the validity of the changes in one study [147] are hard to determine, as only a subset of the participants were investigated following the preseason. Furthermore, in both studies the initial performance level was indicative of an untrained population and increases in performance were relatively small. Several studies have observed no differences in lower-body strength [7, 150], lower-body power [150], aerobic capacity [149], or anaerobic capacity [147] following a professional ballet schedule. The identified studies, therefore, concur with several cross-sectional studies of professional ballet dancers reporting aerobic capacities comparable to non-endurance trained athletes [136, 144], and lower-limb strength values below those of other athletic populations [146]. Therefore, it seems likely that supplementary physical training is needed to elicit significant physiological adaptation.

Improvements in physical performance following the end of a ballet season have been demonstrated in one study [147], in which lower-body strength, lower-body power, flexibility, and aerobic capacity all improved following a six-week summer break. Detraining effects might typically be expected following the cessation of the season [159]. Instead, an improvement in physical performance may be indicative of recovery from non-functional overreaching, or overtraining syndrome [160], which may relate the high volumes of physical work completed in ballet companies [5]. Future research involving concurrent measurements of workload and physical performance across the course of a season may be helpful in further elucidating this relationship.

Investigations into changes in body composition in response to professional ballet reported mixed results. Three studies observed no changes in body composition [7, 146, 147], one saw small increases in lean body mass over a 17-day period spanning a performance period [140], and another saw decreases in body mass and body fat percentage over the course of a season [148]. There was, however, some evidence suggesting female dancers were not adequately meeting their nutritional requirements [140, 148], consistent with previous cross-sectional research in this population [161]. Two included studies also identified the limited opportunity dancers are given to refuel throughout the working day [141, 142]. Dancers have previously been identified as an at-risk group for relative energy deficiency in sport [162]. Given the potential consequences for multiple physiological systems, and for both health and performance [162], ballet companies should ensure they are facilitating screening and monitoring processes and promoting good day-to-day nutritional practices or guidelines.

3.5.4 Methodological Quality

Only five of the 22 studies were classified as *good*, and no studies were classified as *excellent* following the Downs and Black assessment. Similarly, only one study [148] received a 'yes' across all of the five criteria outlined in the MMAT. The most common reason that studies were marked down was the lack of description of the method used to sample participants. Most studies appear to have used a convenience sample of dancers from a single ballet company. When generalizing results to another company, the reader should, therefore, consider the degree of similarity between the company on which the study was completed, and the company to which the results are being extrapolated. Ballet companies are likely to differ widely in factors such as their size, repertoire, and touring schedule, all of which may influence the physical demands faced by dancers. For studies which investigated the demands of performance roles [125, 137, 46], it is difficult to ascertain the extent to which the measured roles are representative of all roles. The potential researcher bias stemming from a lack of random sampling should also be considered, as researchers may have consciously or unconsciously chosen to analyze more physically demanding roles.

The quality of analysis across the included studies was inconsistent. Only two [139, 141] of the 22 included studies included a power calculation, and eight [4, 125, 136, 139, 141, 145, 148, 149] studies used inappropriate or no statistical analyses. Fifteen studies did not include confounding factors in their analysis; this was most often a failure to account for the dancers' company ranks. Those authors who included company rank as a covariate observed significant differences across levels [15, 46, 137, 141, 142].

Due to the mixed quality of included studies, the heterogeneity of subject areas, and the lack of replicated studies, few findings are supported by strong levels of evidence. Ballet staff and researchers should consider the number and quality of studies supporting an outcome when implementing findings.

3.5.5 Limitations

Four databases, the reference lists of included studies, and the reference lists of relevant review articles were searched to conduct a comprehensive literature search. However, it is possible that studies from journals which are not indexed were not identified. Given the artistic nature of the field, we also acknowledge that much of the knowledge regarding the physical demands faced by professional ballet dancers may be published in non-scientific literature. Furthermore, as only published research was included, this review may be limited by publication bias. We were also unable to include articles not written in English; given the popularity of ballet around the globe this may have led to the exclusion of relevant articles. Finally, whilst standardized templates were used, only one reviewer completed data extraction and critical appraisals.

3.5.6 Practical Applications and Further Research

The results of this review reinforce previous suggestions that professional ballet dancers should be considered athletes. Most notably, dancers complete large durations of rehearsal and performance, during which the are required to complete intermittent activity of mixed intensities, characterized by frequent jumps, *pliés* and lifts. Science and medicine practitioners working in professional ballet companies should implement strategies to alleviate the increases in injury risk that may be associated with these demands. For example, encouraging appropriate nutrition and rest following performance, managing dancer training loads, and developing physical characteristics such as strength, power, and aerobic and anaerobic capacity. Given that ballet activity alone does not appear to elicit meaningful physiological adaptations, professional ballet companies should ensure they are providing both the opportunities and resources for dancers to engage in supplementary physical training.

Several key areas of research have not yet been investigated. Research into the session-specific demands of professional ballet has failed to address rehearsals and has not adequately investigated the demands of performance. Understanding these demands more thoroughly may aid in the periodization of repertoire and rehearsals, and provide direction to the physical preparation of dancers. Despite the prominence of *pointe* work in the movement of female dancers, and its implication in foot and ankle injury risk [163, 164]. no studies were identified investigating *pointe* activity during any session type. Finally, whilst several studies identified the large training loads undertaken by dancers as a key physical demand, no studies have investigated how these training loads fluctuate based on the time point in the season or the production being rehearsed or performed. Furthermore, only global measures of activity (e.g., duration, physical activity level) have been used to quantify training loads—several studies [112, 113, 114] have demonstrated the use of wearable sensors to provide more detailed insight into the musculoskeletal demands of ballet, though algorithms are not yet available open-source, and have yet to be used in professional ballet research.

3.6 Conclusions

This study systematically reviewed research investigating the physical demands of professional ballet. Professional ballet activity is characterized by frequent jumps, *pliés*, and lifting movements, as well as high rehearsal and performance exposure time. To ensure dancers are physically prepared for these demands, ballet companies should provide opportunities and resources for supplementary physical training. Future research should focus on the physical demands of rehearsals and the longitudinal training load characteristics of professional ballet. There is a need for greater methodological rigour in this field of research, particularly regarding analysis of data and sampling procedures.

CHAPTER 4

Dance Exposure, Individual Characteristics, and Injury Risk in Professional Ballet: A Five Season Cohort Study

4.1 Abstract

Aim: To describe the relationships between dance exposure, dancer characteristics, and injury risk across five seasons in a professional ballet company. **Methods:** Dance exposure time and clinician-reported time-loss and medical attention injury data were prospectively collected from 118 professional dancers of The Royal Ballet between 2015/16 and 2019/20. Cox proportional hazards and shared frailty models were fitted to overuse and traumatic injuries; age, sex, company rank, injury history, and individualized robust Z-scores for 7-day and 28-day accumulated exposure, and week-to-week change in exposure were included as time-varying covariates. **Results:** Across 381,710 h of exposure, 1332 medical attention (427 time-loss) injuries were observed. Positive relationships were observed between week-to-week change in exposure and overuse time-loss (+1 Z-score hazard ratio: 1.27, 95% confidence interval (CI): 1.06–1.53) and medical attention injury risk (+1 Z-score hazard ratio: 1.17, 95% CI: 1.06–1.28). A negative relationship was observed between 7-day exposure and overuse medical-attention injury risk (+1 Z-score hazard ratio: 0.74, 95% CI: 0.66–0.84). Overuse time-loss injury risk was greater in soloists compared to the *corps de ballet* (hazard ratio: 1.47, 95% CI: 1.01–2.15), and in dancers with a higher previous injury rate (+1 injury·1000 h^{-1} hazard ratio: 1.06, 95% CI: 1.02–1.10). Only age was associated with traumatic time-loss (+1-year hazard ratio: 1.05, 95% CI: 1.01–1.09) or medical attention injury risk (+1-year hazard ratio: 1.04, 95% CI: 1.01–1.07). **Conclusions:** Professional ballet companies should implement training principles such as periodization and progression, particularly for dancers with multiple risk factors. These findings provide a basis for future prospective investigations into specific causal injury pathways.

4.2 Introduction

Sports science and medicine departments operate with the twin goals of maximising performance and reducing the risk of athletic injury [19]. Understanding the load-injury relationship is, therefore, fundamental when planning training programmes, such that technical and physical qualities can be developed without excessively increasing the risk of injury [9]. The mismanagement of workload may lead to maladaptive responses such as non-functional overreaching, overtraining syndrome, and injury [23, 17]. The International Olympic Committee position stand on load and injury risk in sport identifies a need for research into specific athletic populations [17]. Despite multiple studies suggesting workload may be a risk factor for injury in professional ballet [141, 165, 166], the load-injury relationship has not yet been investigated in this population.

Professional ballet companies perform as many as 145 shows per season, comprised of up to 18 productions [14]. To prepare for the physical, technical, and artistic demands of these performances, professional ballet dancers rehearse for 3.5–9.0 h per day [5]. Weekly dance exposures are, therefore, regularly above 30 $h \cdot wk^{-1}$ [167], exceeding training and competition exposures reported in elite sporting environments [155, 156]. Furthermore, whereas sportspeople typically taper their training before competition [168], a ballet company will instead increase rehearsal load in the build-up to the opening night of a production [149]. This increase may reflect limited access to theatre stage space, and an effort to improve the execution of the ballet prior to performance.

Several studies have investigated the load-injury relationship in the wider field of dance [122, 123, 169], however, inappropriate statistical methods (e.g., Pearson's correlation) or underpowered study designs have been used. Conversely, Jeffries et al. [121] detailed the workloads and injury events of 16 contemporary dancers across one year, to guide future large-scale prospective studies. Whilst the prospective design used in this study is favourable, the resulting small sample size meant that the authors could not determine associations between load and injury risk. The shortcomings of study designs using existing data in load-injury research have been well discussed [94]. Nonetheless, the use of existing data can provide direction to prospective investigations, whilst overcoming the sample size limitations faced by short-term prospective research.

The aim of this study was, therefore, to describe the relationships between dance exposure, dancer characteristics, and injury risk across five seasons in a professional ballet company.

4.3 Methods

4.3.1 Study Design and Setting

The present study is secondary use of data [170] recorded as part of a five-year prospective study which aimed to describe the incidence rate, severity, and burden of time-loss and medical attention injury at The Royal Ballet between August 8$^{\text{th}}$, 2015, and March 15$^{\text{th}}$, 2020 [163]. All data were prospectively recorded, and all dance events took place at the Royal Opera House, London. Where applicable, the STROBE-SIIS statement has been used to guide the reporting of this study [171].

4.3.2 Participants

As part of normal working practices, data were collected from 119 eligible dancers across the ranks of *apprentice*, *artist*, *first artist*, *soloist*, *first soloist*, and *principal*: 108 participants gave written informed consent. The remaining 11 were contacted: 10 did not respond and one declined to participate. A legitimate interest assessment was completed, and written support from both the Data Controller and Clinical Director of the company was provided to use anonymized data pertaining to the 10 participants who could not be contacted. This was approved by the local ethics committee in accordance with the Declaration of Helsinki. Demographics of the included 118 dancers (age 26.9 ± 7.3 y) are provided in Table 4.1.

4.3.2.1 Company Rank

Ballet companies are hierarchical, with each dancer assigned a rank. The rank of apprentice is given to dancers in their first year of professional employment. Apprentices, artists, and first artists make up the *corps de ballet*, who typically perform as an ensemble. Dancers can be promoted to the ranks of soloist and first soloist, where they will perform increasingly featured roles. Finally, principal dancers are the most senior, performing leading roles. Promotions typically take place at the conclusion of the season. Roles may be fluid across ranks (e.g., some first soloists may perform Principal roles).

4.3.3 Injury

Injury data were recorded by in-house medical staff (Chartered Physiotherapists: five full-time, one part-time, eleven covering staff leave, and two who were consulted to provide

Table 4.1: Demographics of the sample for each season in the study. Brackets indicate the ranks of participants who chose not to take part in the study.

Demographic	2015/16	2016/17	2017/18	2018/19	2019/20
All	83	87	82	90	91
Left the cohort	-	6	13	3	5
Joined the cohort	-	10	8	11	6
Female					
Apprentice	2	4	3	4	4
Artist	11	11	10	13	12
First Artist	9	10	11	10	12
Soloist	11	9	8	4	5
First Soloist	7	7	6	9	9
Principal	6	8	8	8	8
Male					
Apprentice	3	4	4	4	2
Artist	7	7	7	10	11
First Artist	5	6	6	7	7
Soloist	8 (1)	7 (1)	7	7	8
First Soloist	7	5	4	5	5
Principal	7	9	8	9	8

historical data; medical doctors: 4 part-time) using the Orchard Sports Injury Classification System [172]. In line with previous recommendations [173], both medical attention and time-loss injuries were included in this study. Medical attention injuries were defined as "any musculoskeletal complaint that required medical attention from a healthcare professional" [173]. In line with previous research and consensus statements in professional ballet [14, 15], association football [174], and rugby union [175], time-loss injuries were defined as "any injury that prevented a dancer from taking a full part in all dance-related activities that would normally be required of them for a period equal to or greater than 24 hours after the injury was sustained" [14, 15]. Injuries were classified as either overuse or traumatic based on the nature of onset: overuse injuries were defined as "any medical incident that did not have a sudden onset from a discrete event" [176], whilst traumatic injuries were defined as any medical incident that had a sudden onset from a specific identifiable event.

4.3.4 Dance Exposure Time

An online athlete management system (Smartabase v.6.5.11, Fusion sport, Brisbane, Australia) was used to record class and rehearsal exposure time [177]. During each week in the study, the company's Artistic Scheduling Manager entered an individualized schedule for each dancer, detailing their class and rehearsal timetable for the following week. Performance exposure time was estimated from electronic copies of casting sheets from each of the five seasons. Hard copies of the casting sheet for each performance were examined to ensure any last-minute casting changes were amended. For each day in the study, participants' total ballet class, rehearsal, and performance exposure time was calculated.

For each participant, and each day in the study, accumulated dance exposure time over the previous seven days (i.e. day -1 to day -7; *7-day exposure*), accumulated dance exposure time over the 28 days preceding those seven days (i.e. day -8 to day -35; *28-day exposure*) [106], and the *week-to-week change* in dance exposure time (i.e., day -1 to day -7 minus day -8 to day -14) were estimated. These periods were chosen because they are the most frequently used periods in this field of research [73, 78].

For each participant, individualized robust Z-scores [178] were calculated for each dance exposure time variable using the equation:

$$\textit{robust Z score} = \frac{\textit{variable - individual median}}{\textit{individual median absolute deviation}}$$

4.3.5 Age, Sex, Injury History, and Company Rank

Participant age, sex, and injury history were included as covariates in the analysis, having been identified as injury risk factors in sport and dance [179, 180, 181]. Injury history was included in the form of each dancer's historical injury rate within the data set, per 1000 h of dance exposure. For company rank, a categorical variable was included, where participants were classed as *corps de ballet* members (apprentices, artists, and first artists), soloists (soloists and first soloists), or principals.

4.3.6 Statistical Analysis

Associations between dance exposure variables and time-loss and medical attention injury incidence were investigated by fitting Cox proportional hazards and shared frailty models to the data using the R package *survival* [182]. The count of injury events per predictor parameter [183] was: time-loss overuse - 17.6 events, time-loss traumatic - 12.9 events, medical attention overuse - 70.1 events, and medical attention traumatic injuries - 25.0 events. An insufficient number of injury events were recorded to further subdivide injuries by tissue type. Daily dance exposure time was entered as the timescale variable and participant identity was entered as the frailty term, accounting for repeated events within individuals and heterogeneity in baseline risk with the shared frailty model. Separate cause-specific hazard models were fitted for overuse and traumatic injuries. Exposure periods which ended with either no injury or with a different injury classification were right-censored [184]. Week-to-week change in dance exposure, 7-day accumulated dance exposure, and 28-day accumulated dance exposure were entered as time-varying covariates. In line with previous suggestions to investigate non-linear relationships between training load and injury, quadratic and cubic terms were included in the model [65, 185]. Hazard ratios associated with individual characteristics were investigated by including participant age, sex, company rank, and injury history as variables in each model.

To compare the goodness of fit of the Cox proportional hazards models against the shared frailty models, analysis of deviance tables were constructed using the R function *anova.coxph*. Log-likelihoods, Akaike information criteria, and Bayesian information criteria were calculated, with values closer to zero indicative of better model fits. The proportional hazards assumption for each model was confirmed using the R function*cox.zph*. Individual predictor variables were determined to have reached statistical significance at $p < .050$; given the exploratory nature of the present investigation, no multiplicity adjustments were made for multiple outcomes [99]. Hazard ratios for significant dance exposure variables were simulated and plotted with 50% and 95% shortest probability intervals using the R package *simPH* [186]. Hazard ratios reported are indicative of a one median absolute deviation increase in the predictor variable, unless otherwise stated. All statistical analyses took place in R (version 4.0.3, R Foundation for Statistical Computing, Vienna, Austria).

4.4 Results

A total of 1547 medical attention injuries, of which 516 were time-loss injuries, were recorded across the five seasons; 135 medical attention injuries, including 59 time-loss injuries, were excluded because they occurred when a dancer was not engaged in a normal rehearsal schedule (e.g., during rehabilitation, sabbatical, maternity, etc.). Eighty medical attention injuries (two bone, one central/peripheral nervous system, 40 joint/ligament, seven muscle/tendon, and 29 'other'), including 30 time-loss injuries (two bone, 17 joint/ligament, one muscle/tendon, and 10 'other') were excluded because records indicated that a physiotherapist had not classified the injury as either overuse or traumatic. The final dataset, therefore, consisted of 1332 medical attention (overuse: 982; traumatic: 350) and 427 time-loss (overuse: 246; traumatic: 181) injuries across 381,710 h of dance exposure.

4.4.1 Overuse Injuries

A positive linear relationship was observed between overuse medical attention injury rate and week-to-week change in accumulated exposure (hazard ratio: 1.17, 95% CI: 1.06–1.28, p = .001; Figure 4.1), whilst a negative linear relationship was observed between overuse medical attention injury rate and 7-day accumulated exposure (hazard ratio: 0.74, 95% CI: 0.66–0.84, $p < .001$; Figure 4.1). Overuse medical attention injury rate was greater in soloists (hazard ratio: 1.29, 95% CI: 1.02–1.62, p = .034) but not principals (hazard ratio: 1.34, 95% CI: 0.96–1.87, p = .081) compared to the *corps de ballet*, and lower in males compared to females (hazard ratio: 0.79, 95% CI: 0.64–0.97, p = .026).

The shared frailty model revealed a positive linear association between week-to-week change in accumulated exposure and overuse time-loss injury rate (hazard ratio: 1.27, 95% CI: 1.06–1.53, p = .011; Figure 4.2). No significant linear or non-linear relationships were observed between overuse time-loss injury and 7-day or 28-day accumulated exposure time. Injury history was positively associated with overuse time-loss injury, with an increase of one injury per 1000 h resulting in a hazard ratio of 1.06 (95% CI: 1.02–1.10, p = .005). An increase in overuse time-loss injury rate was observed in the soloist group compared to the *corps de ballet* (hazard ratio: 1.47, 95% CI: 1.01–2.15, p = .045), though no significant difference in overuse time-loss injury rate was observed between the *corps*

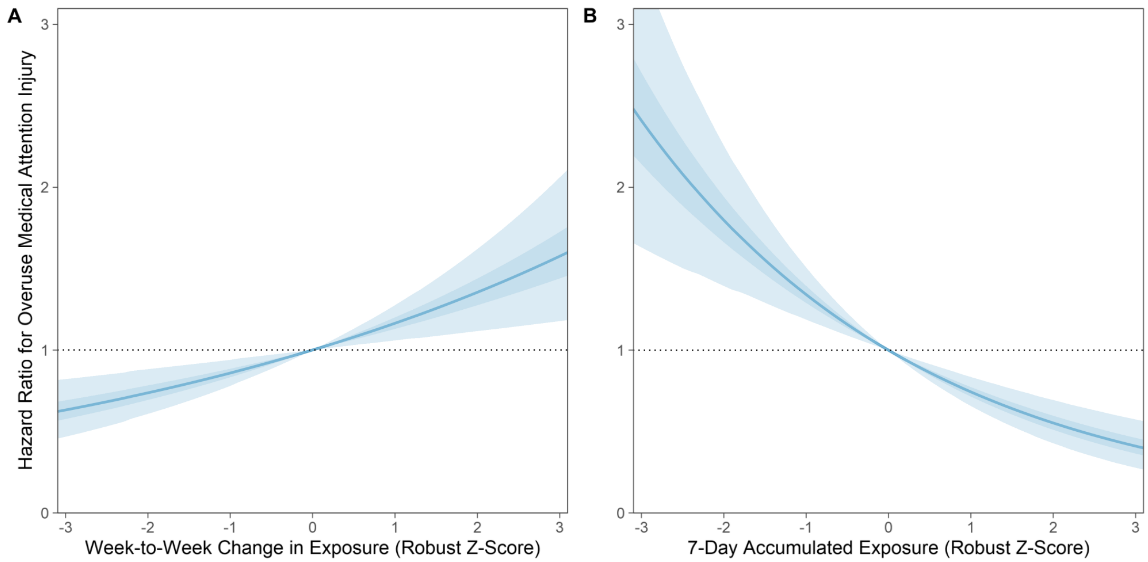


Figure 4.1: Significant linear associations between A) week-to-week change in dance exposure time and overuse medical attention injury risk, and B) 7-day accumulated exposure and overuse medical attention injury risk. The central line represents the median of all simulations, whilst the darker and lighter areas represent the 50% and 95% shortest probability intervals, respectively.

de ballet and principal dancers (hazard ratio: 1.40, 95% CI: 0.81–2.41, p = .230). No significant associations were observed between overuse time-loss injury rate and either age (hazard ratio: 1.00, 95% CI: 0.96–1.03, p = .840) or sex (male hazard ratio: 0.91, 95% CI: 0.66–1.26, p = .580).

4.4.2 Traumatic Injuries

For traumatic medical attention injuries, a significant association was only observed with age (+1-year hazard ratio: 1.04, 95% CI: 1.01–1.07, p = .016). A large but non-significant difference in traumatic medical attention injury rate was observed in principals compared with the *corps de ballet* (hazard ratio: 1.51, 95% CI: 0.95–2.41, p = .083).

No dance exposure variables were associated with traumatic time-loss injury rate. A cubic relationship between 28-day accumulated exposure and traumatic time-loss injury rate demonstrated the best fit to the observed data of any dance exposure time variable but was not statistically significant (p = .053; Figure 4.3). Hazard ratios for traumatic time-loss injury were greater for soloists and principals compared with the *corps de ballet*, though were not significant (principals hazard ratio: 1.57, 95% CI: 0.92–2.68, p = .096; soloists hazard ratio: 1.36, 95% CI: 0.90–2.06, p = .140). A significant increase in traumatic time-

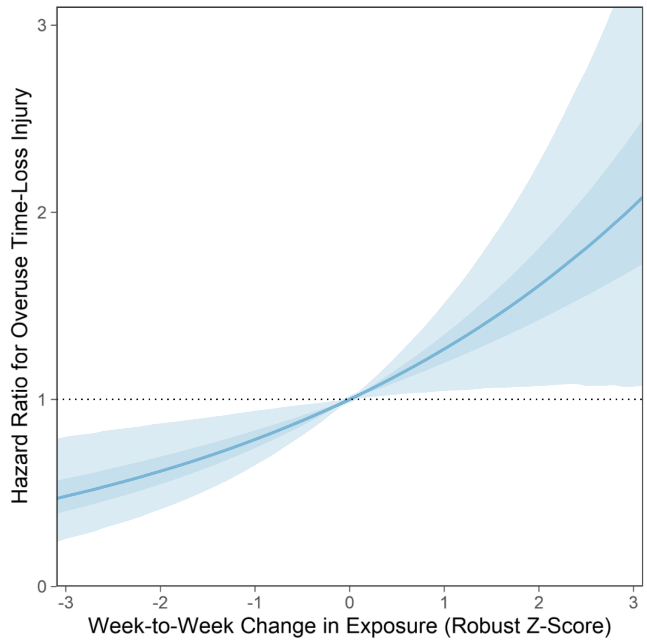


Figure 4.2: Significant positive linear association between week-to-week change in dance exposure time and overuse time-loss injury risk. The central line represents the median of all simulations, whilst the darker and lighter areas represent the 50% and 95% shortest probability intervals, respectively.

loss injury was observed with increasing age (+1-year hazard ratio: 1.05, 95% CI: 1.01–1.09, p = .005), however, no association was observed between traumatic time-loss injury rate and injury history (+1 injury·1000 h^{-1} hazard ratio: 1.02, 95% CI: 0.96–1.09, p = .500) or sex (male hazard ratio: 0.95, 95% CI: 0.70–1.31, p = .772).

4.4.3 Model Fit

For both overuse and traumatic injuries, and for both medical attention and time-loss injuries, shared frailty models indicated better fits to the observed data than Cox proportional hazard models (Table 4.2).

4.5 Discussion

This is the first study to investigate relationships between dance exposure and medical attention and time-loss injury risk in professional ballet. In line with previous recommendations [76, 187], we fitted shared frailty models to a dataset of 381,710 exposure hours, 1332 clinician-reported medical attention injuries, and 427 clinician-reported time-loss injuries

Table 4.2: Model selection criteria for the Cox proportional hazards and shared frailty models.

Model	Model Selection Criteria		
	LL	BIC	AIC
Overuse Time-loss			
Cox PH	-1046.6	2170.2	2121.1
Shared Frailty	-1005.0[B]	2258.7	2100.3
Overuse Medical Attention			
Cox PH	-4205.7	8507.9	8439.5
Shared Frailty	-4101.5[B]	8702.9	8348.1
Traumatic Time-loss			
Cox PH	-755.6	1584.1	1539.3
Shared Frailty	-738.8[A]	1628.6	1533.2
Traumatic Medical Attention			
Cox PH	-1477.3	3036.7	2982.7
Shared Frailty	-1416.7[B]	3157.9	2944.2

[A] Significant ($p < .010$) improvement compared with Cox PH model.
[B] Significant ($p < .001$) improvement compared with Cox PH model.
AIC, Akaike information criterion; BIC, Bayesian information criterion; LL, log-likelihood; PH, proportional hazards.

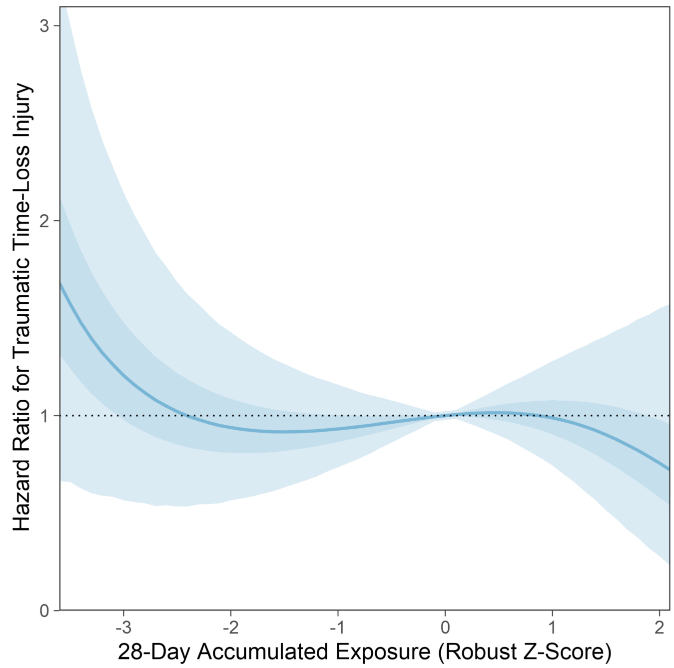


Figure 4.3: Non-significant quadratic association between 28-day accumulated dance exposure time and traumatic time-loss injury risk. The central line represents the median of all simulations, whilst the darker and lighter areas represent the 50% and 95% shortest probability intervals, respectively.

to identify potential risk factors for injury. Overuse time-loss injury rate was associated with week-to-week change in dance exposure, company rank, and injury history, whilst traumatic time-loss and medical attention injury rates increased with age but were not associated with any other variables. Ballet companies can manage potential injury risk factors by implementing training principles such as periodization and progressive overload.

In the present results, week-to-week increases in dance exposure were positively associated with the rate of overuse injury. This finding agrees with several studies identifying excessive increases in load as a potential risk factor for athletic injury [73, 90]. Furthermore, dancers have suggested that injury is related to a lack of consistency in workload, resulting from factors such as a congested performance schedule, or an increase in stage calls before an opening night [12, 149]. Although the aetiological role that a spike in workload may play in injury has been speculated, causal mechanisms have not yet been established. Several frameworks for overuse injury outline an interplay between structure-specific load and structure-specific load capacity [72]. In the current results, dance exposure may be a surrogate measure of the former, with large week-to-week increases in exposure representing an increase in load beyond the tolerance of any given tissue—at present, however, this is speculative. It is also important to note that given the non-linear relationship between the magnitude of a loading stimulus and the resulting tissue damage [67], using dance exposure as a proxy for tissue damage in any one specific dancer, at a single point in time, is likely futile. Instead, when scheduling rehearsals and performances, professional ballet companies should employ company-wide and season-long strategies that alleviate sharp increases in dance exposure; for example, distributing workload uniformly across the company, periodizing the repertoire, or progressing loads gradually before congested periods of performances.

No associations were observed between 28-day accumulated dance exposure and either overuse or traumatic injury rate in the present results, consistent with recent research in professional soccer [95]. Research in rugby union [76] and cricket [188], however, has suggested that low chronic workloads are indicative of undeveloped physical qualities, whilst high chronic workloads are indicative of well-developed physical qualities, and subsequently robust athletes. Although the direction of the relationship between 28-day accumulated dance exposure and traumatic injury rates supports this hypothesis, the strength of the relationship does not; ultimately, our results do not justify conclusive statements on this topic. Future investigations into chronic workloads and injury risk should account for confounders; for example, periods of low chronic exposure likely occur at the beginning of the season (following reduced strength training, or concurrent with large increases in load), or following rehabilitation from an injury (when affected tissues may still be remodelling). Contrasting multiple studies that have identified high acute workloads as a potential injury risk factor in sportspeople [9], we report no association between 7-day accumulated exposure and either overuse or traumatic time-loss injury risk in professional ballet dancers. These results support previous suggestions that high workloads alone are not problematic; instead, the risk of injury is influenced by the manner in which an athlete progresses to those high workloads [16]. When scheduling rehearsal and performances, however, ballet companies should consider that whilst time-loss injury incidence rates may not increase with high acute loads, the absolute number of time-loss injuries will likely increase proportionally with exposure time. Surprisingly, the hazard ratio for overuse medical attention injuries was greatest following lower seven-day accumulated exposures, contradicting an established paradigm for athletic injury risk [16].

In agreement with previous investigations in pre-professional ballet [189], we observed an increased rate of time-loss overuse injury in dancers with a higher prior injury incidence [179, 190]; however, no evidence was observed for any relationship between injury history and traumatic time-loss or medical attention injuries. In contrast, the rate of traumatic injury, but not overuse injury, increased with age. When interpreting this result, it is important to consider not only the physiological effects of aging but also the contextual implications; for example, age is positively associated with company rank. Furthermore, within company-ranks the casting of different roles, and subsequently a dancer's activity, may be influenced by age. Consistent with previous research in professional ballet and modern dancers [191], we observed differences in injury risk across company ranks, as soloists demonstrated significant increases in overuse injury compared to *corps de ballet* dancers. This finding may reflect the fact that senior-ranking dancers are typically cast in more physically demanding roles [46], and work at higher activity intensities [141, 192] compared to their junior counterparts. Despite the differences in the activity and biomechanical demands of typical male and female roles [46], no differences in either overuse or traumatic time-loss injury risk were observed between sexes; a lower hazard ratio for overuse medical attention injuries, however, was observed in males compared with females.

4.5.1 Strengths, Limitations, and Considerations

This is the largest investigation to date into potential risk factors for injury in professional ballet. Both the number of participants and injuries in the present study exceed sample sizes often used in similar sporting research; nonetheless, the injury count was insufficient to subcategorize injuries by tissue type. Several reviews have recommended the time-to-event models used in the present analysis for sports injury research, allowing for time-varying covariates, recurrent events, cause-specific hazards [187, 97].

Whilst the secondary use of data facilitates the large sample size, it has several implications for the findings. Firstly, the results are not evidence of a causal link between dance exposure and injury risk [193]; the present design is unable to account for several potential confounding factors, for example, confounding via the schedule [100]. Retrospective studies have been highlighted as being at-risk of researcher bias, in part due to the flawed selection of multiple or seemingly arbitrary time windows [94]. Without being able to pre-register analyses before data collection, we have, therefore, used the most commonly investigated time windows from this research field in an attempt to alleviate this limitation.

Although exposure data were prospective, individualized, and recorded by a single individual, it was not possible to calculate each dancer's exact time involvement in performances. Furthermore, we could not include all possible exposure, for example as a result of private rehearsal, or teaching. We must, therefore, accept that some level of error in the calculation of exposure time. Although injury data were recorded by 23 different clinicians over the five seasons, 98% of injuries were recorded by five primary physiotherapists and all injuries were entered using a standardized form. We must acknowledge, however, that the recording of injury data may not have been entirely uniform. We also had to exclude eighty medical attention injuries due to a lack of classification; no analysis was performed to assess the impact of this exclusion.

Finally, it is important to highlight the shortcomings of time exposure as a measure of athletic load compared to quantifications of volume and intensity. Whilst these measures are regularly collected in sport, they are not yet commonplace in dance environments, particularly in a company of this size. We also acknowledge several contextual factors that may contribute to injury risk which are not quantified, for example, variations in choreographic genres, the differing demands of class, rehearsal, and performance, and the psychological load associated with live performance.

4.5.2 Future Research and Practical Applications

This study provides a platform from which future prospective observational and experimental studies in professional ballet may develop causal injury pathways. In line with existing aetiological frameworks [72], measurements of both structure-specific load and structure-specific load capacity should underpin research in dance [20]. To facilitate this research, the development of more advanced measures of physiological tissue forces outside of a laboratory is required. Given that the development of physical qualities may be more practical than manipulating rehearsal and performance load, understanding the role of structure-specific load capacity may be particularly valuable.

Increases in injury rate were associated with larger week-to-week increases in dance exposure, agreeing with several previous investigations in sport, though it should be noted that research in this field has yielded mixed results. Whilst specific thresholds with which to manipulate a dance schedule are not warranted based on the current results, they do support the use of established training principles. At present, it appears to be rare for a ballet schedule to include meaningful recovery periods or facilitate progressions in load; instead, training loads are highly variable because of factors such as studio, stage, or choreographer availability, changes in casting due to injury, and unequal distribution of work both between and within company ranks. Artistic and medical staff working in professional ballet companies should be mindful of excessive progressions in load, therefore, rehearsal and performance schedules should be periodized when planning a repertoire. Practically, this may entail strategies such as the gradual progression of load before congested periods of performances; providing regular periods of offload to facilitate recovery; or organizing the repertoire such that the most physically demanding productions are not performed consecutively, or by the same primary casts. This may be particularly relevant for higher-risk dancers, i.e., senior-ranking dancers, dancers with a higher rate of previous injury, or older dancers. To manage risk factors associated with variations in training load, further research is required to better understand the schedules undertaken by professional ballet dancers.

4.6 Conclusion

In a five-season cohort study in a professional ballet company, increases in overuse time-loss injury rate were associated with week-to-week increases in dance exposure, injury history, and the company ranks of soloist and first soloist. Traumatic injury rate was associated with age, but no dance exposure variables or dancer characteristics. These results provide a basis for the development of causal pathways in future prospective studies. Science and medicine practitioners and artistic staff working in professional ballet should consider the training principles of progression, periodization, and recovery when planning rehearsal and performance schedules.

CHAPTER 5

Rehearsal and Performance Volume in Professional Ballet: A Five-Season Cohort Study

5.1 Abstract

Introduction: Few studies have published data concerning the longitudinal rehearsal and performance demands experienced by professional ballet dancers. The aim was to describe the rehearsal and performance volumes undertaken across five professional ballet seasons, and identify factors associated with inter-dancer and inter-production variation in dance hours. **Methods:** Scheduling data were collected from 123 dancers over five seasons at The Royal Ballet. Linear mixed effects models were used to evaluate differences in: i) weekly dance hours and seasonal performance counts across sexes, company ranks, and months, and ii) factors associated with the variation in rehearsal hours required to stage different productions. **Results:** On average across the five seasons, a peak in performance volume was observed in December, whereas rehearsal hours peaked in October and November, and between January and April. Differences in weekly dance hours were observed between company ranks ($p < .001$, range in means: 19.1–27.5 h·week^{-1}). Seasonal performance counts varied across company ranks ($p < .001$), ranging from 28, 95% CI [22, 35] in principals, to 113, 95% CI [108, 118] in the rank of artist. Accumulated rehearsal durations were considerably greater in preparation for newly created ballets compared with existing ballets (77.8 vs 37.5 h). Rehearsal durations were also greater in preparation for longer ballets, with each additional minute of running time associated with a 0.43 h increase in rehearsal duration ($p < .001$). Full-length ballets, however, were consistently the most time-efficient to stage due to their long performance runs compared with shorter ballets (16.2 vs 7.4 performances). **Conclusions:** Training principles such as progressive overload and periodization should be implemented in professional ballet companies to manage the high and variable rehearsal and performance loads.

5.2 Introduction

To provide effective support services to dancers, science and medicine practitioners must understand the physical demands undertaken by those dancers [194]. The acute activity demands of ballet have been relatively well described; ballet is intermittent [125], with an activity profile comparable to basketball [153] and tennis [195]. Performances are comprised of short durations of high-intensity movement interspersed with periods of low-intensity activity, during which a dancer may be in character or off-stage [46]. Within a performance, dancers are required to execute highly technical jumps, lifts, and balances, requiring strength, power, flexibility, and motor control [6]. The demands of a ballet schedule over months, and years, however, have not yet been explored.

To date, no study has investigated the rehearsal or performance schedules of a professional ballet company beyond a three-week period. Several studies report superficial descriptive data regarding the structure of a ballet schedule: companies perform ~145 shows per season, comprised of ~15 different productions, and weekly dance hours are between 30–40 h [15]. It is unclear, however, in how many of these shows individual dancers perform, in how many of the productions individual dancers are cast, and how much intra-individual, inter-individual, and seasonal variation in dance hours exists. Furthermore, no study has investigated the rehearsal periods required to stage specific productions, nor the factors which may influence these rehearsal periods.

Several position stands and consensus statements have been published relating to longitudinal workload in sport, and its relationships with performance, overtraining, injury, and illness [196, 17]. Despite suggestions that ballet, like sport, should embrace established training principles [147, 108], the absence of published longitudinal data relating to the structure of a ballet season makes it challenging to implement periodization strategies. In the present study a five-season data set of the ballet class, rehearsal, and performance exposure scheduled by an elite professional ballet company is explored. Measures of exposure—although not accounting for exercise intensity—have been shown to be important variables to monitor in sport [76, 197, 198], whilst the previous chapter revealed excessive week-to-week changes in dance exposure to be associated with injury risk in professional ballet [199].

The first aim was to describe the structural characteristics of a professional ballet season; namely, rehearsal hours and performance counts, intra-season variation, and repertoire make-up. The second aim was to identify factors related to the variation in rehearsal hours across different productions.

5.3 Methods

5.3.1 Participants

The initial sample were 124 dancers of The Royal Ballet; 108 gave written informed consent, one declined, and 15 did not respond. To use anonymized data pertaining to the 15 participants who could not be contacted, a legitimate interest assessment was completed to ensure data protection regulations were met, following which written support from both the Data Controller and Clinical Director of the company was provided. This was approved by the local ethics committee in accordance with the Declaration of Helsinki. A total of 123 dancers (women: n = 66, 28.0 ± 8.3 y; men: n = 57, 27.9 ± 8.5 y) were, therefore, included in this study. A breakdown of the distribution of company ranks across each of the five seasons is presented in Table 5.1.

Table 5.1: Demographics of the sample for each of the five seasons.

Demographic	2015/16	2016/17	2017/18	2018/19	2019/20
All	88	91	90	99	99
Female					
Apprentice	2	4	3	4	4
Artist	11	11	10	14	12
First Artist	9	10	11	10	12
Soloist	11	9	8	4	5
First Soloist	7	7	6	9	9
Principal	6	8	8	8	8
Principal Character Artist	2	1	3	3	3
Male					
Apprentice	3	4	4	4	2
Artist	7	7	7	10	11
First Artist	5	6	6	7	7
Soloist	8 (1)	7 (1)	7	7	8
First Soloist	7	5	4	5	5
Principal	7	9	8	9	8
Principal Character Artist	3	3	5	5	5

5.3.2 Design

A descriptive cohort design was used to explore the structure of a professional ballet season, using data collected for a larger prospective study [163]. Ballet classes, rehearsals and performances taking place at the Royal Opera House, London, were prospectively recorded as part of normal working practices between the 2015–16 and 2019–20 seasons.

5.3.3 Data Collection

Three session types were included in this study: *Class* – typically the first session of a dancer's day, focusing on ballet technique; *Rehearsal* – a session during which dancers will be learning or practicing choreography for a specific ballet; and *Performance* – a single show on the main stage for which a public audience is present. Throughout this study the term Production is also used, referring to the ballet being performed (e.g., Romeo and Juliet, The Nutcracker, etc.). Class and rehearsal data were recorded by the company's Artistic Scheduling Manager. Data were entered once a week using a bespoke athlete management system (Smartabase, Fusion Sport, Brisbane, Australia). Performance data were recorded using casting sheets; both electronic and hard copies were filed following each performance. It was beyond the scope of the available data to determine the exact duration for which each role was involved in a performance; as a result, dancers were assigned 3 h of exposure time for a performance—the duration for which they are scheduled to be in attendance. Scheduling data for touring periods were incomplete, and were, therefore, excluded from this study. Touring periods were typically 4 weeks in duration during June and July, immediately following the conclusion of the 2015–16 to 2018–19 seasons.

Throughout the data collection period, time-loss injury data were recorded to the athlete management system by in-house Chartered Physiotherapists. For analyses of weekly dance hours and week-to-week changes in dance hours, data points were removed from the analysis when the dancer was designated as injured for more than two days in a week. For seasonal performance counts data points were removed from the analysis when the dancer was designated as injured for more than 10% of days during the season. These decisions were made such that data reflected the demands of an uninjured dancer's schedule.

5.3.4 Data Processing

Following the conclusion of the 2019–20 season, all scheduled class and rehearsal data between 4th August 2015 and 15th March 2020 were exported from the athlete management system. Performance involvements were determined by manual inspection of hard copies of casting sheets, ensuring all last-minute casting changes were accounted for. Neither electronic nor hard copies of casting sheets were available for 8 performances (1.2% of all performances). No action was taken to impute data. Scheduling data were subsequently used to calculate the summary variables, defined in Table 5.2. For seasonal performance

Table 5.2: Definitions of calculated variables.

Variable	Definition
Weekly dance hours	The sum of scheduled dance hours in a dancer-week.
Seasonal performance count	The count of performances in a dancer-season.
Week-to-week change	The difference in a dancer's weekly dance hours compared to the previous week.
Individual rehearsal hours	The rehearsal hours completed by a dancer in preparation for a specific production.
Company rehearsal hours	The total rehearsal hours completed by all dancers in preparation for a specific production (i.e., the sum of individual rehearsal hours for a given production).
Production time-efficiency	The ratio of company rehearsal hours to the total on-stage performance time resulting from the production (i.e., company rehearsal hours / [number of performances × performance duration]).

counts, data from the 2019–20 season were excluded from the analysis due to being cut short because of the COVID-19 global pandemic.

5.3.5 Statistical Analysis

To investigate differences in weekly dance hours across sexes, company ranks, and months, and differences in seasonal performance counts across sexes and company ranks, linear mixed effects models were implemented using the *lme4* R package [200]. Sex, company rank, and month were entered as fixed effects, whilst within-individual grouping and season were entered as random effects. Bonferroni adjusted pairwise comparisons of estimated marginal means were used to compare differences across sex, rank, and month. Significance was accepted at $p < .025$, accounting for two primary outcomes.

To investigate factors associated with the individual rehearsal hours required to stage a production, a linear mixed effects model was used. Dancer (company rank, sex, performance count) and performance characteristics (production running time, years since last staged, existing ballet or newly created choreography) were entered as fixed effects, whilst within-individual grouping and production were entered as random effects. Where significant effects were observed, estimated marginal mean rehearsal hours were extracted from the model and compared graphically. For each model, the assumptions of normality, linearity, and homoscedasticity were confirmed. Data are reported as mean ± SD. Data processing and analyses were conducted using R v.4.0.3 (R Foundation for Statistical Computing, Vienna, Austria).

5.4 Results

All seasons ran from August to June, except for 2019–20 which concluded prematurely in March due to the COVID-19 global pandemic. Touring periods immediately followed the final week of each season (mean duration 28 ± 4 days). A representative timeline of a season is shown in Figure 5.1. The company staged 10.5 ± 0.8 (range: 9–11) productions per season, comprised of 18.3 ± 1.6 (range: 16–20) separate ballets. The company performed totals of 133, 135, 138, 132, and 94 (+43 cancelled) shows in the 2015–16 to 2019–20 seasons, respectively. Ninety-eight out of 365 dancer-seasons and 1,767 out of 15,837 dancer-weeks were removed from the analysis due to injury.

The mixed effects model investigating weekly dance hours revealed significant main effects of company rank ($p < .001$; Figure 5.2-A), month (Figure 5.3; $p < .001$), and company rank × month interaction ($p < .001$), but no effect of sex (female 22.8 h, 95% CI [22.0, 23.6]; male 23.9 h, 95% CI [23.1, 24.7]; $p = .049$) or sex × company rank interaction ($p = .348$). The mixed effects model investigating seasonal show count revealed a significant main effect of company rank ($p < .001$; Figure 5.2-B), but no effect of sex (female 73.5 shows, 95% CI [69.5, 77.4]; male 76.2 shows, 95% CI [72.3, 80.1]; $p = .338$), or sex × company rank interaction ($p = .689$). The distribution of increases in week-to-week change in weekly dance hours across all recorded dancer-weeks is presented in Figure 5.4.

The individual rehearsal hours, company rehearsal hours, and production time-efficiency for all productions staged across the five seasons are presented in a supplementary file (Appendix E). The mixed effects model investigating factors associated with individual rehearsal hours revealed significant main effects of: years since the production was last staged ($p < .001$); production duration ($p < .001$); and an interaction effect of company rank × new or existing ballet ($p < .001$), but no association was observed with sex ($p = .119$), or the number of performances of the production completed by the dancer ($p = .960$). The mean number of individual rehearsal hours associated with each significant independent variable is presented in Figure 5.5.

5.5 Discussion

This study explored five seasons of rehearsal and performance scheduling data at a professional ballet company; this is the first study investigating the longitudinal working demands of a professional ballet company for a period beyond three weeks. Mean weekly dance hours were between 19.1 and 27.5 h, though weeks involving > 40 h of scheduled dance were common; large variations in weekly dance hours were evident both between and within company ranks and months of the season. Alongside this study we provide company rehearsal durations for specific productions, and the time-efficiency of those productions. Dancers involved in newly created ballets appear to complete considerably more rehearsal than they might in an existing work, warranting offload from other productions. These results are the first to investigate the structure of a ballet season, and may be useful for staff when periodizing repertoire, casting productions, or planning late-stage rehabilitation for dancers following injury.

Mean weekly dance hours were between 19.1 and 27.5 h, exceeding training and competition durations reported in elite rowing [201], rugby union [155], and track and field [202]. Whilst it is important to acknowledge that the present data lacks a measure of intensity, and is, therefore, not a comprehensive measure of training load, the extent to which these values exceed those in sporting contexts is notable. Even the highest daily durations reported in sport [155, 201, 202] fall at the lower end of those observed in the present study. These dance volumes likely underpin the reduction in physical performance observed at the conclusion of a ballet season [147], and the high rate of burnout in classical dance [203]. Large variation in weekly dance hours was evident across the cohort; the 'worst-case-scenario' [204] for a dancer may, therefore, be ~50 h of scheduled dance in a week. In a rehabilitation context, medical staff should consider whether a dancer is prepared to tolerate this volume of work before returning to full rehearsal. In the previous chapter, greater hazard ratios for injury risk were observed with greater progressions in training volume. The frequency of large week-to-week increases in dance hours should, therefore, be a cause for concern [89, 90]; this is particularly the case as it would be unlikely for intensity to be adjusted in response to increases in exposure in this environment. In keeping with well-established principles of training, ballet companies should avoid scheduling large spikes in rehearsal and performance volume where possible.

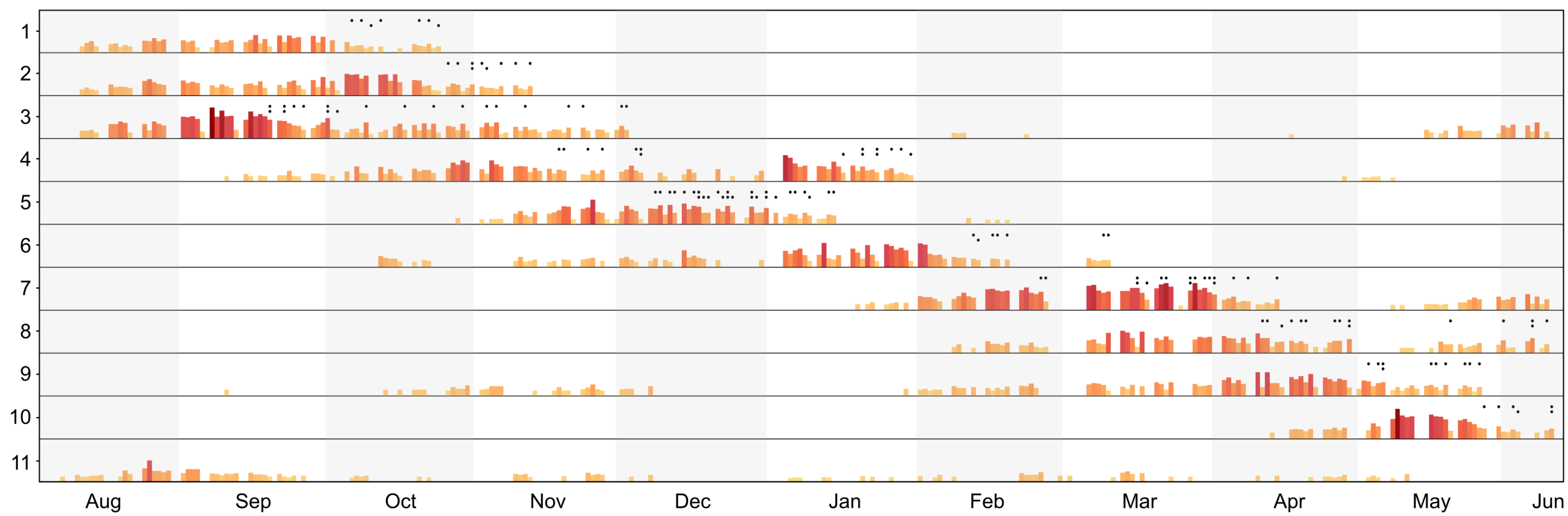


Figure 5.1: Timeline of a representative season, illustrating the distribution of rehearsal and performance hours across the repertoire. Column height and darkness represent the daily rehearsal time for the production, whilst lower and upper dots indicate matinees and evening performances, respectively.
1 - Raven Girl / Connectome; 2 - Viscera / Carmen / Afternoon of a Faun / Tchaikovsky *Pas de Deux*; 3 - Romeo and Juliet; 4 - Monotones / Rhapsody / The Two Pigeons; 5 - The Nutcracker; 6 - After the Rain / Strapless / Within the Golden Hour; 7 - Giselle; 8 - The Winter's Tale; 9 - Frankenstein; 10 - Obsidian Tear / The Invitation / Within the Golden Hour; 11 - Non-main rep.

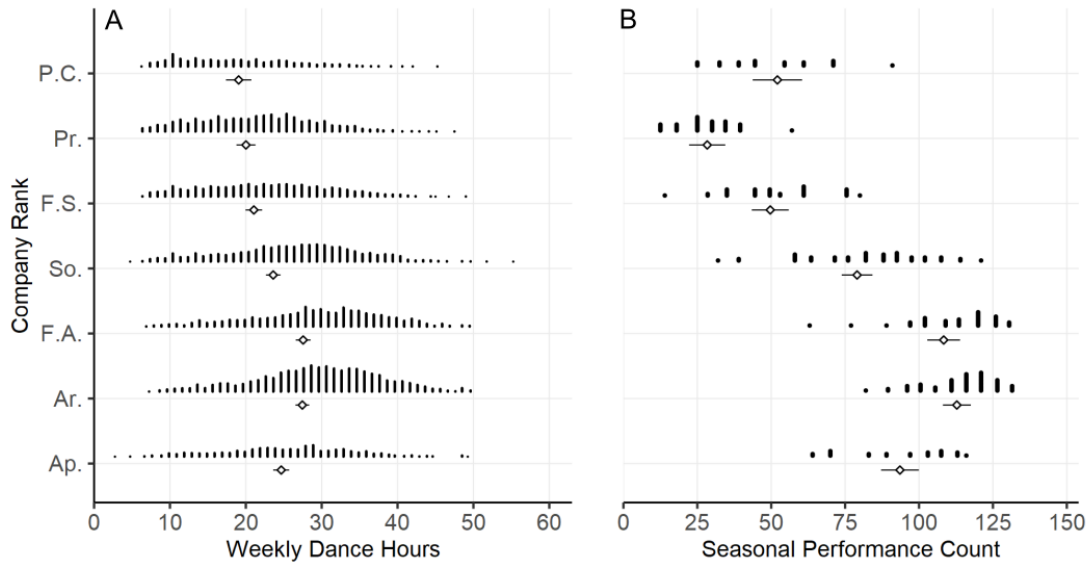


Figure 5.2: A) Weekly dance hours and B) seasonal performance counts, by company rank. Diamonds and bars indicate the estimated marginal mean and 95% confidence intervals extracted from mixed effects models. Ap., apprentice; Ar., artist; F.A., first artist; So., soloist; F.S., first soloist; Pr., principal; P.C., principal character artist.

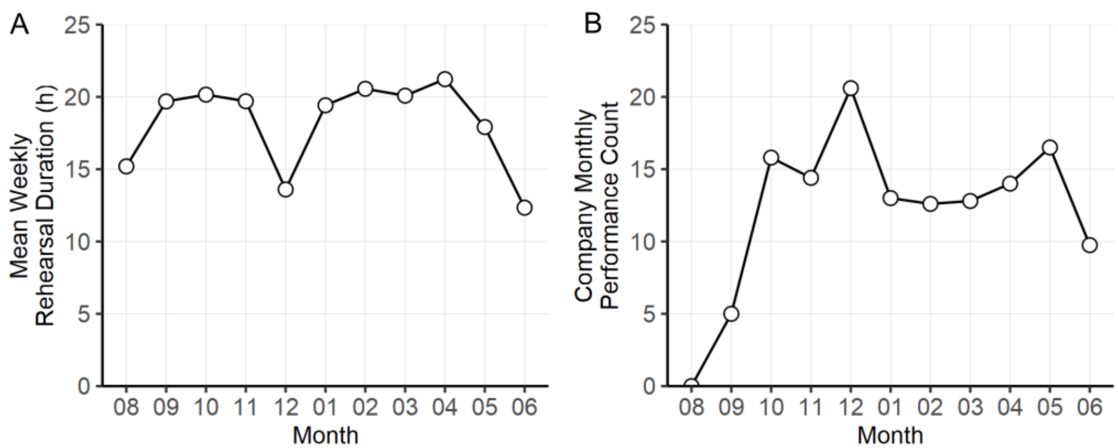


Figure 5.3: A) Mean weekly rehearsal hours and B) total number of performances staged by the company for each month in the season.

Large variations in weekly dance hours were observed both within, and between company ranks. As dancers are promoted from apprentice through the ranks of artist and first artist, greater weekly dance durations and seasonal show counts are evident. As dancers are promoted beyond the *corps de ballet*, however, dance volume is incrementally reduced. Junior company members have previously been shown to spend less time active across the day compared with soloists and principals [142]. Thus, it seems probable that as a dancer's

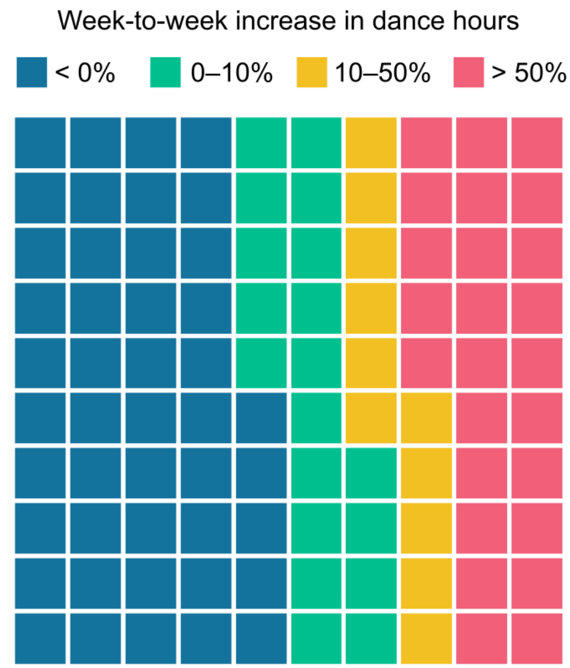


Figure 5.4: Week-to-week increases in dance hours across the company. Each square represents 1% of dancer-weeks in the dataset.

rank progresses, their volume of work decreases whilst the intensity of their work increases [46]. The transition from pre-professional to professional ballet has been identified as a potential period of heightened injury risk due to increased ballet exposure [165]. However, similar weekly dance hours were observed in apprentices as those previously reported in pre-professional dancers [205], suggesting this transition is not accompanied by an increase in dance exposure. No difference in dance hours was observed between sexes. Scheduled dance time, therefore, appears to be broadly comparable between male and female dancers, though in specific companies, and at specific timepoints, these values are likely to fluctuate based on the repertoire, casting, and company demographic.

Ballet exposure and performance frequency fluctuated across the course of each season. The relatively low dance exposure recorded in September reflects the absence of performances, as well as efforts to incrementally increase load in response to research identifying this period as one of heightened injury risk [206]. Despite the increase in show count, December sees a reduction in dance hours across all company ranks. This reflects the staging of *The Nutcracker* in four of the five seasons, a production which is highly time-efficient. Thus, a regular and well-established ballet requiring relatively little rehearsal, in combination with a long performance run, may be a useful tool by which to de-load rehearsal volume. Dance volume was highest in October and November, and from January to April.

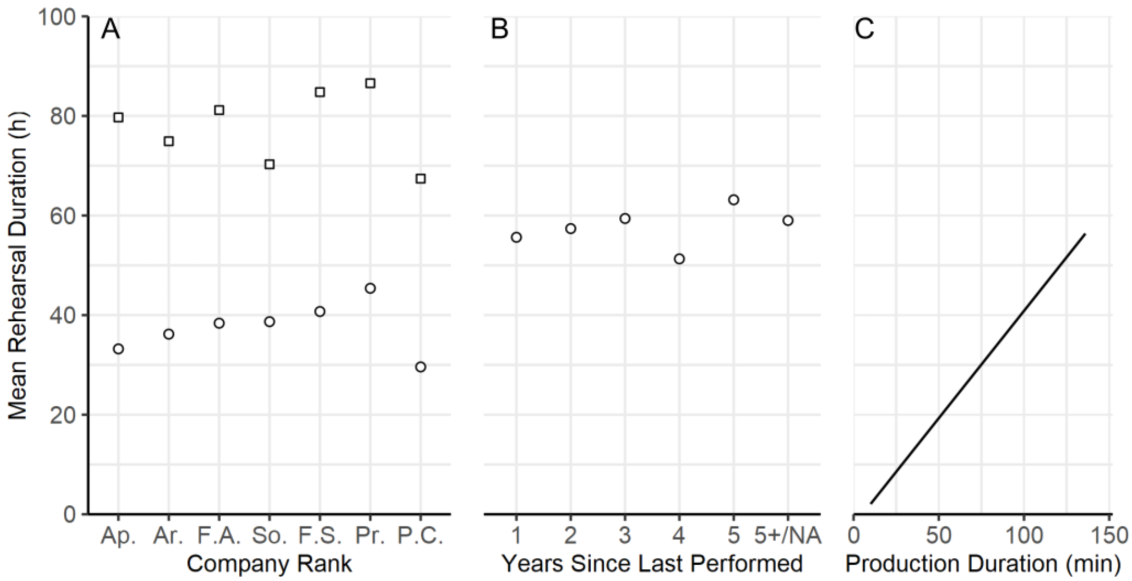


Figure 5.5: Associations between A) company rank, B) the number of years since a production was last staged, or C) the running time of a performance, and the mean rehearsal duration completed by a dancer in preparation for a production. In panel A, squares represent new ballets, whilst circles represent existing ballets. Ap., apprentice; Ar., artist; F.A., first artist; So., soloist; F.S., first soloist; Pr., principal; P.C., principal character artist.

These months likely reflect 'normal' in-season volumes, compared with the 'low' months discussed above.

For the first time, this study investigated the duration of rehearsal completed in preparation for individual productions, and explored factors associated with the variation in these durations. Whilst it is unsurprising that greater rehearsal hours were observed in preparation for longer productions, full length productions were in fact time-efficient to stage, primarily due to the large number of performances which took place during runs of those productions compared with shorter ballets (16.2 vs 7.4 performances per production). Newly created ballets were typically the least time-efficient to stage, reflecting the additional time required to choreograph and subsequently learn the production. It is evident from the individual rehearsal hours completed in preparation for a newly created ballet that individuals involved in the creation of a ballet complete greater volumes of rehearsal. Consideration should be given to the concurrent roles in which these dancers are cast; where possible, companies should consider offloading other roles to ensure their work is manageable. Finally, despite their lower weekly dance hours, senior-ranking dancers typically complete greater rehearsal hours than junior-ranking dancers for individual productions (Figure 5.5); their lower weekly ballet exposure is, therefore, a result of being cast in fewer productions.

5.5.1 Practical Applications and Future Research

In line with previous recommendations, the present results provide a basis for the periodization of rehearsal and performance volume throughout a professional ballet season [108]. For example, specific applications of these results include: providing periods of volume offload by scheduling time-efficient productions amongst inefficient ones; forecasting the required rehearsal hours of a production to facilitate a gradual progression in ballet volume in advance of the start of rehearsals; planning an incremental return-to-dance during rehabilitation; and periodization of the repertoire to avoid periods of rehearsal and performance congestion.

Several specific ballets warrant discussion. Firstly, full-length classical ballets such as *The Nutcracker, Romeo and Juliet*, *Manon* and *The Sleeping Beauty* were highly time-efficient to stage due to their long performance runs, and frequent appearances season-to-season. To this end, even full-length new creations such as *Swan Lake* and *Frankenstein*, which incurred by far the largest company rehearsal hours, were relatively time-efficient to stage because of their long performance runs. Mixed bills comprised of several shorter ballets typically required the most rehearsal hours relative to the resulting performance time. In the instance that one of those shorter ballets is a new creation, an effort should be made to account for the resulting increase in rehearsal volume by pairing it with more time-efficient productions.

Further research into the scheduling demands—or better still, the training loads—experienced by professional ballet dancers at other dance companies or schools may be beneficial for science and medicine practitioners seeking to optimize rehearsal and performance schedules. In particular, this may be useful for touring companies which operate under separate rehearsal and performance periods [15], or for ballet schools, in which the demands experienced by a student may change year-on-year. For high quality research to take place in this area, valid measures of training load in dance must be developed.

5.5.2 Strengths and Limitations

Strengths of this study include the five-year dataset; the entry of all class and rehearsal sessions by a single individual; the use of a standardized entry form to record class and rehearsal data; and the high availability of casting sheets. Several limitations of the data should be acknowledged. Firstly, the study is limited by a lack of an intensity measure, therefore, workload cannot be fully understood across this period. Although data describing both the volume and intensity of activity are commonplace in sporting research, this level of data is not yet routinely collected in professional ballet companies due to the large number of dancer, limited resources, cultural challenges, and individualized schedules. The present data, therefore, represents a considerable progression in the quality of longitudinal data in this field. There was no register of attendance taken at rehearsals—it is unlikely though, that dancers would not have attended rehearsals for which they were scheduled. It was beyond the scope of the available data to break down every individual performance role across the study period. A dancer's level of involvement within a show, or within specific productions in a mixed bill, could, therefore, not be ascertained. Finally, the lack of scheduling data during touring periods is a limitation, as this represents a considerable volume of rehearsal and performance.

It is important to note that differences exist between companies in the rehearsal and performance schedule structure, and the casting of productions. Science and medicine practitioners working in professional ballet should, therefore, consider the degree of similarity between companies when applying these results.

5.6 Conclusion

Over a five-season period in a professional ballet company, large and variable rehearsal and performance volumes were observed. Artistic staff and science and medicine practitioners should be mindful of large week-to-week variability in dance hours, the high volumes of work associated with new productions, and congested periods of dance exposure in the latter stages of the season. Training principles such as periodization and progression should be implemented to manage these demands. Absolute and relative rehearsal and performance volumes should be considered when planning repertoire, casting ballets, and scheduling rehearsals and performances.

CHAPTER 6

The Validity of the Session Rating of Perceived Exertion Method for Measuring Internal Training Load in Professional Ballet Dancers

6.1 Abstract

Aim: The aim of this study was to investigate the convergent validity of s-RPE with objective measures of internal training load in professional classical ballet dancers. **Methods:** Heart rate and s-RPE data were collected in 22 professional classical ballet dancers across a total of 218 ballet class or rehearsal sessions. Eleven participants completed at least 9 sessions, and were, therefore, included in analyses of individual relationships between s-RPE and objective measures. To calculate s-RPE, the session duration was multiplied by the rating of perceived exertion, measured using the modified Borg CR-10 scale. The e-TRIMP and b-TRIMP methods were used as criterion measures of internal training load. Pearson product-moment correlation coefficients were used to determine intra-individual relationships between s-RPE and objective measures. Repeated measures correlations (r_{rm}) were used to identify intra-individual relationships common across the cohort. **Results:** Positive linear relationships were observed between s-RPE and objective measures across all session types (e-TRIMP: $r_{rm\ (195)} = 0.81$, $p < .001$; b-TRIMP: $r_{rm\ (195)} = 0.79$, $p < .001$), in ballet class (e-TRIMP: $r_{rm\ (58)} = 0.64$, $p < .001$; b-TRIMP: $r_{rm\ (58)} = 0.59$, $p < .001$), and in rehearsals (e-TRIMP: $r_{rm\ (119)} = 0.82$, $p < .001$; b-TRIMP: $r_{rm\ (119)} = 0.80$, $p < .001$), as well as across both males (Edwards TRIMP: $r_{rm\ (136)} = 0.82$, $p < .001$; b-TRIMP: $r_{rm\ (136)} = 0.80$, $p < .001$) and females (e-TRIMP: $r_{rm\ (57)} = 0.80$, $p < .001$; b-TRIMP: $r_{rm\ (57)} = 0.78$, $p < .001$). Intra-individual correlation coefficients ranged from 0.46 – 0.96 (e-TRIMP: mean r = 0.81 ± 0.11, $p = .051 - < .001$; b-TRIMP: mean r = 0.78 ± 0.14, $p = .130 - < .001$). **Conclusions:** These results demonstrate that s-RPE is a valid and practical method for measuring internal training load in professional classical ballet dancers.

6.2 Introduction

Classical ballet is an intermittent activity, consisting of high intensity explosive actions interspersed with periods of lower intensity technical movements or inactivity [46]. Each season, a professional ballet company may perform as many as 145 shows of 15 different productions [15]. To prepare for the performance schedule, professional dancers will typically complete 1.5 h of ballet class, and between 2 and 7 h of rehearsals each working day [5]. The resulting training volume is greater than values previously reported in elite team sport [207] and endurance athletes [208], and has been linked with overtraining and injury [108]. The periodization of training load has been proposed as a strategy to optimize performance and reduce the risk of overuse injury within dance populations [108].

Training load can be described in terms of the physical work performed during exercise, or the psychophysiological responses to that work, i.e., the external and internal training load, respectively [18]. It is the internal training load, however, which provides the stimulus for physiological adaptation. A valid measure of internal training load in ballet is, therefore, essential for understanding the training stimulus experienced by a dancer, and manipulating rehearsal and performances schedule appropriately. Dance intensity during ballet rehearsal and performance has previously been measured using $\dot{V}O_2$, HR, and [BLa] [4]. Given the number of dancers employed by professional companies and the aesthetic demands of ballet performance, these solutions are impractical for daily monitoring. The s-RPE method, derived from the product of session duration and RPE, has, therefore, been used as a time-sensitive and cost-effective method of quantifying internal training load in dance populations [158]. Simple derivatives such as monotony and strain may subsequently provide practitioners with insights into maladaptive responses to training such as overtraining and illness. The s-RPE method is, therefore, commonly used in both research and applied practice, and has been validated across a range of modalities including team [36], combat [209], and endurance sports [156]. Although the validity of s-RPE has been demonstrated in populations of contemporary [109, 110] and step dancers [210], to our knowledge it has not been investigated within ballet dancers.

Jeffries et al. [109] investigated relationships between s-RPE and objective measures of internal training load in contemporary dancers during contemporary class, contemporary rehearsal, and ballet class. Group correlations ranging from 0.44–0.73 and 0.52–0.72 were observed for contemporary class and rehearsal, respectively, while relationships were weaker in ballet class ($r = 0.32$–0.58). Similarly, in a cohort of pre-professional contemporary dancers, Surgenor and Wyon [110] saw a strong group correlation ($r = 0.72$) between contemporary class and rehearsals, but a moderate relationship ($r = 0.46$) in ballet class alone. The weaker relationships observed in ballet class compared with rehearsals could have been because ballet was not the dancers' primary genre, or because of a difference in the genres themselves. These distinctions between dance/genre specific sessions (i.e., ballet class versus rehearsal) are consistent with research in sporting contexts [211, 212]. Furthermore, factors such as the athlete's sex, age, and fitness level have all been suggested to influence the relationship between s-RPE and objective measures of training load [39].

Investigations into the influence of sex on the perception of exercise have demonstrated mixed results. While no difference in RPE was observed between male and female college students during a graded exercise test [213], male and female champion cross country runners registered differing perceptions of 'hard' sessions [214]. Within classical ballet, the roles and technical choreographies performed differ across sex. Male dancers are required to lift their partners, demanding significant full body strength and control [46]. Conversely, female dancers are required to dance *en pointe*, placing stress on the foot and ankle [215]. In this regard, male and female roles are comprised of sufficiently different demands to be considered separate modalities. It is, therefore, important to understand the extent to which s-RPE is a valid measure of internal training load in both male and female dancers.

The primary aim of this study was to investigate the construct validity of s-RPE as a measure of internal training load in professional classical ballet dancers, by examining its convergence with two validated training load measures derived from HR. The secondary aim was to understand the effect of session type and sex on this relationship.

6.3 Methods

6.3.1 Participants

A sample of 13 male (25.5 ± 5.3 years, 179.7 ± 4.0 cm, 73.2 ± 5.2 kg, 7.8 ± 5.6 years professional) and 9 female (25.2 ± 4.4 years, 164.0 ± 3.3 cm, 52.9 ± 4.1 kg, 7.4 ± 4.2 years professional) dancers from a professional ballet company volunteered to take part in the study. The sample consisted of dancers of the following ranks within the company hierarchy: one apprentice (1F), seven artists (4M 3F), five first artists (2M 3F), three soloists (3M), four first soloists (2M 2F), and two principal dancers (2M). Prior to the onset of data collection, participants were given a full written explanation of the study aims and protocol and gave written informed consent. The protocol was approved by the local board of ethics in accordance with the Declaration of Helsinki.

6.3.2 Experimental Design

A correlational study design was employed between April and October, 2019. Participants were given the freedom to select the days during which data collection would take place. Heart rate and s-RPE data were collected following the final session of each day. Edwards summated HR zones (e-TRIMP) [31] and Banister training impulse (b-TRIMP) [216] were calculated as criterion measures of internal training load, consistent with previous validations of s-RPE. It should, therefore, be noted that the criterion measures were primarily measures of aerobic demand, and not of other physiological demands (e.g., anaerobic, neuromuscular). Throughout the data collection period participants completed their normal rehearsal schedules as prescribed by the company's artistic staff. For analyses of intra-individual relationships between measures, in order to achieve sufficient power to identify any convergence greater than r = 0.50, a sample of 23 sessions per participant was required ($\alpha = 0.05$, $\beta = 0.80$, r = 0.50). Collecting this volume of data was impractical in the present cohort; therefore, we present intra-individual correlations where participants exceeded the required sample size for the expected correlation coefficient ($\alpha = 0.05$, $\beta = 0.80$, r = 0.80, n = 9), based on similar investigations [217].

6.3.3 Objective Measures of Internal Training Load

Heart rate data were collected during each session using a Polar H1 sensor (Polar Electro, Kempele, Finland) secured to the chest via an elastic strap and recorded by a wearable activity monitoring unit (ClearSky T6, Catapult Sports, Australia). Polar heart rate sensors have demonstrated correlations of 0.98 with electrocardiography. Following the final session of each day, data were downloaded using Openfield Cloud Analytics software (Catapult Sports, Australia). Individual session data were then exported for external analysis. Peak HR was calculated as the highest of either the age predicted maximum [218] or the peak value recorded during the data collection period. The e-TRIMP was calculated by multiplying the time spent in five HR zones by a corresponding coefficient (50–60% HR_{peak} = 1; 60–70% HR_{peak} = 2; 70–80% HR_{peak} = 3; 80–90% HR_{peak} = 4; and 90–100% HR_{peak} = 5), the results of which were then summed. The b-TRIMP was calculated using the equation:

$$\textit{b-TRIMP} = D \times \textit{HR}_R \times A \times e^{B \times \textit{HR}_R}$$

where D = the session duration, A = 0.64 for men and 0.86 for women, B = 1.92 for men and 1.67 for women, and HR_R was calculated using the equation:

$$HR_R = \frac{HR_{\text{ex}} - HR_{\text{rest}}}{HR_{\max} - HR_{\text{rest}}}$$

where HR_{ex} = mean HR during exercise, HR_{rest} = resting HR, and HR_{peak} = peak HR.

6.3.4 Measurement of Session-RPE

For the measurement of s-RPE, the modified Borg CR-10 scale was used to quantify session intensity [34]. Approximately 15 minutes following the final session of each day, the lead investigator met with each participant individually to record a rating of perceived exertion for each session that day. The use of retrospective RPEs was important to ensure the results were ecologically valid; within large ballet companies, dancers have multiple sessions per day, and may each be on a unique schedule, making it impractical to collect data after each session. Within sporting environments, the use of retrospective s-RPEs has been shown to be methodologically robust [219, 220]. The participant was shown the Borg CR-10 scale and asked about each session in the form of the question: "What was the intensity of your 1 pm rehearsal?". This differs from the original phrasing ("How was your workout?"), with the aim of directing the participant toward giving solely an intensity rating, and not a rating that takes session duration into account [21]. Prior to the onset of the study, participants were educated on the use of the Borg CR-10 and the reporting of session-RPE. Participants were directed to first focus on a descriptive anchor, and then select a corresponding numerical value. If appropriate, participants were given the option to divide the session into multiple sections and give a separate RPE for each. The RPE was multiplied by the session duration (mins) to calculate s-RPE.

6.3.5 Statistical Analysis

Intra-individual relationships were analysed using Pearson's product-moment correlation coefficient. This decision was made despite both s-RPE and objective measures of training load being non-normally distributed, as the rate type 1 error is relatively robust to non-normality when sample sizes are not especially small [221]. This allowed for comparisons to be made with previous investigations into the validity of s-RPE in athletic populations, which have almost exclusively used Pearson's r [39]. To investigate the common intra-individual relationships across the entire cohort, a repeated measures correlation (r_{rm}) [222] was conducted using the R package *rmcorr* [223]. Data were subsequently stratified, and repeated measures correlations were conducted on sub-groups to investigate relationships across sexes (i.e., male and female sub-groups), and across session types (i.e., ballet class and rehearsal sub-groups). Statistical significance was set at $p < 0.05$. In line with previous research [109], the magnitude of the correlation coefficient was interpreted as follows: < 0.10 *trivial*, 0.10–0.29 *small*, 0.30–0.49 *moderate*, 0.50–0.69 *large*, 0.70–0.89 *very large* and 0.90–1.0 *almost perfect*. All analyses were completed using R version 3.5.3 (R Foundation for Statistical Computing, Vienna, Austria).

6.4 Results

Data were collected across of 79 ballet classes and 139 rehearsals. Participants completed a mean of 9.9 ± 7.7 sessions each. Of the initial cohort of 22, 11 participants completed at least 9 sessions, and were, therefore, included in intra-individual analyses. One participant completed only one session, and, therefore, did not qualify for either intra-individual correlation, nor repeated measures correlation. The mean session duration (hh:mm:ss) was 01:12:10 ± 00:09:11, 00:52:31 ± 00:22:19, and 00:59:38 ± 00:20:53 for ballet class, rehearsals, and all sessions, respectively. Descriptive statistics for s-RPE, e-TRIMP, and b-TRIMP are shown in Figure 6.1.

Repeated measures correlations revealed *very large* positive relationships between s-RPE and objective measures across all sessions (e-TRIMP: $r_{rm\ (195)} = 0.81$, $p < 0.001$, 95% CI [0.76–0.86]; b-TRIMP: $r_{rm\ (195)} = 0.79$, $p < 0.001$, 95% CI [0.73–0.84]. *Large* (e-TRIMP: $r_{rm\ (58)} = 0.64$, $p < 0.001$, 95% CI [0.45–0.77]; b-TRIMP: $r_{rm\ (58)} = 0.59$, $p < 0.001$, 95% CI [0.39–0.74]) and *very large* (e-TRIMP: $r_{rm\ (119)} = 0.82$, $p < 0.001$, 95% CI [0.75–0.87]; b-TRIMP: $r_{rm\ (119)} = 0.80$, $p < 0.001$, 95% CI [0.72–0.85]) repeated measures correlations were observed between s-RPE and e-TRIMP in ballet class and rehearsals, respectively. *Very large* repeated measures correlations between s-RPE and objective measures were observed for both male (e-TRIMP: $r_{rm\ (136)} = 0.82$, $p < 0.001$, 95% CI [0.76–0.87]; b-TRIMP: $r_{rm\ (136)} = 0.80$, $p < 0.001$, 95% CI [0.73–0.85]) and female (e-TRIMP: $r_{rm\ (57)} = 0.80$, $p < 0.001$, 95% CI [0.68–0.88]; b-TRIMP: $r_{rm\ (57)} = 0.78$, $p < 0.001$, 95% CI [0.66–0.87]) participants. Results of intra-individual correlations between s-RPE and objective measures are reported in Table 6.1. A comparison of the repeated measures and Pearson's correlation results for each participant are shown in Figures 6.2 and 6.3.

6.5 Discussion

To our knowledge, this is the first study to investigate the validity of s-RPE for the quantification of internal training load within a cohort of professional ballet dancers. The present results demonstrate *large* repeated measures correlations between s-RPE and objective

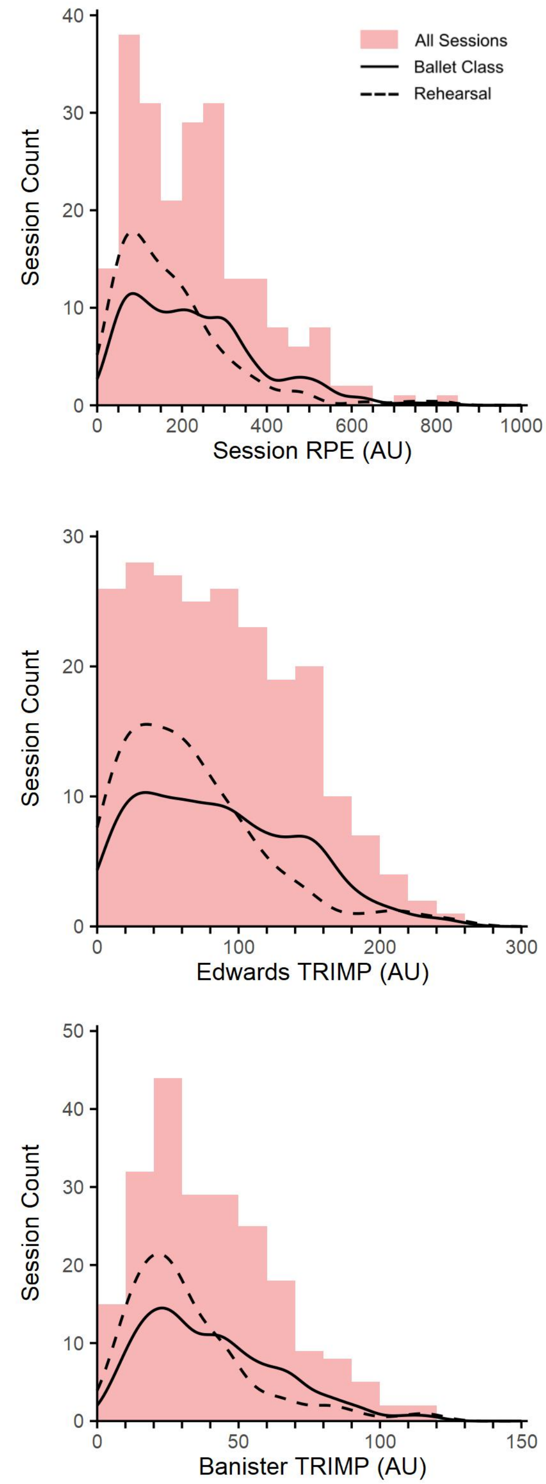


Figure 6.1: The distribution of (A) session rating of perceived exertion (Session RPE); (B) Edwards summated heart rate zones; and (C) Banister training impulse measures during all sessions (red bars), ballet class (solid line), and rehearsals (dashed line).

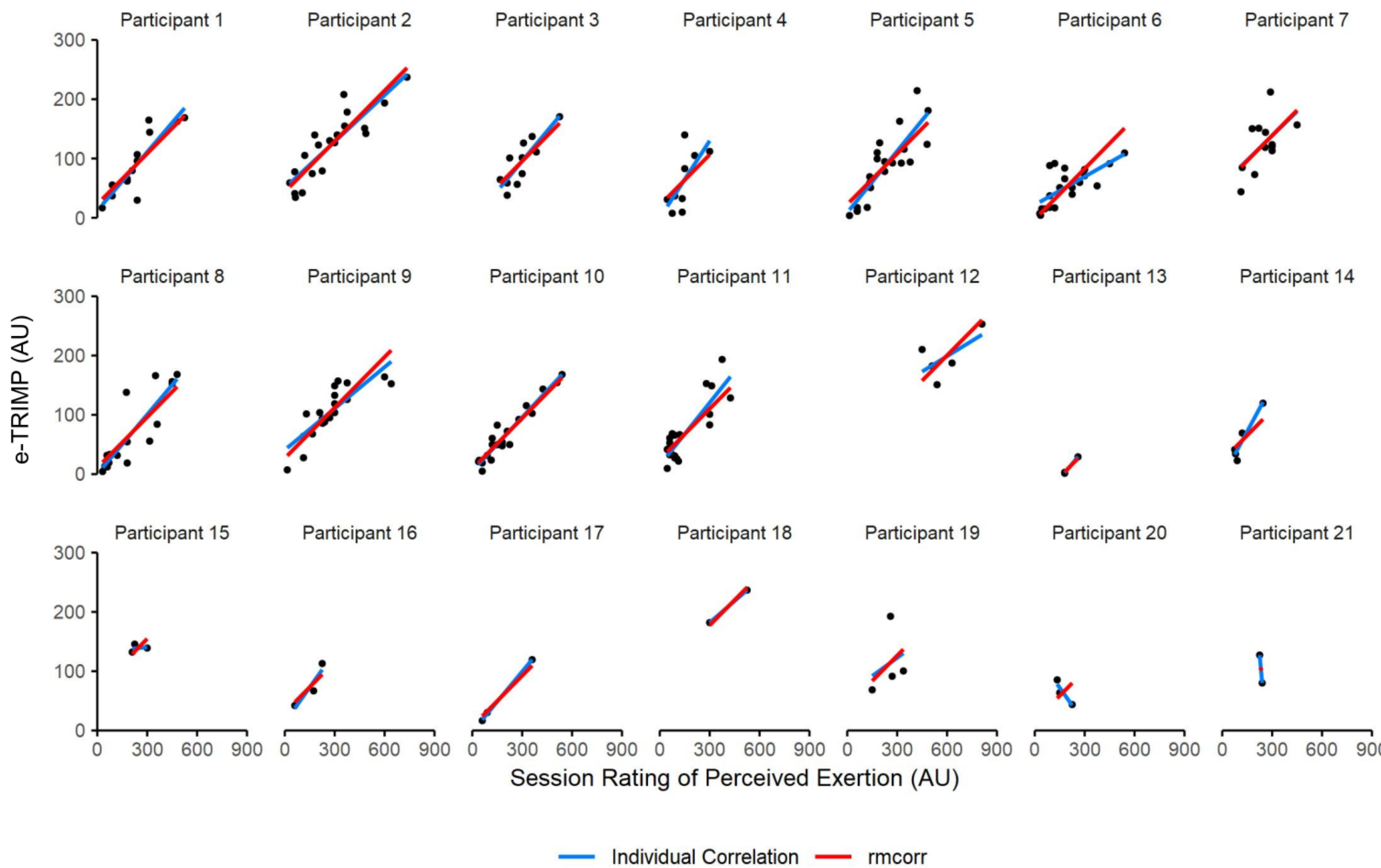


Figure 6.2: A comparison of Pearson's correlation and repeated measures correlation results for relationships between session rating of perceived exertion and Edwards summated heart rate zones (e-TRIMP). Each session completed by a participant is represented by a black circle. Blue lines depict individual Pearson's correlations for each participant. Red lines depict the goodness of the repeated measures correlation fit for each participant.

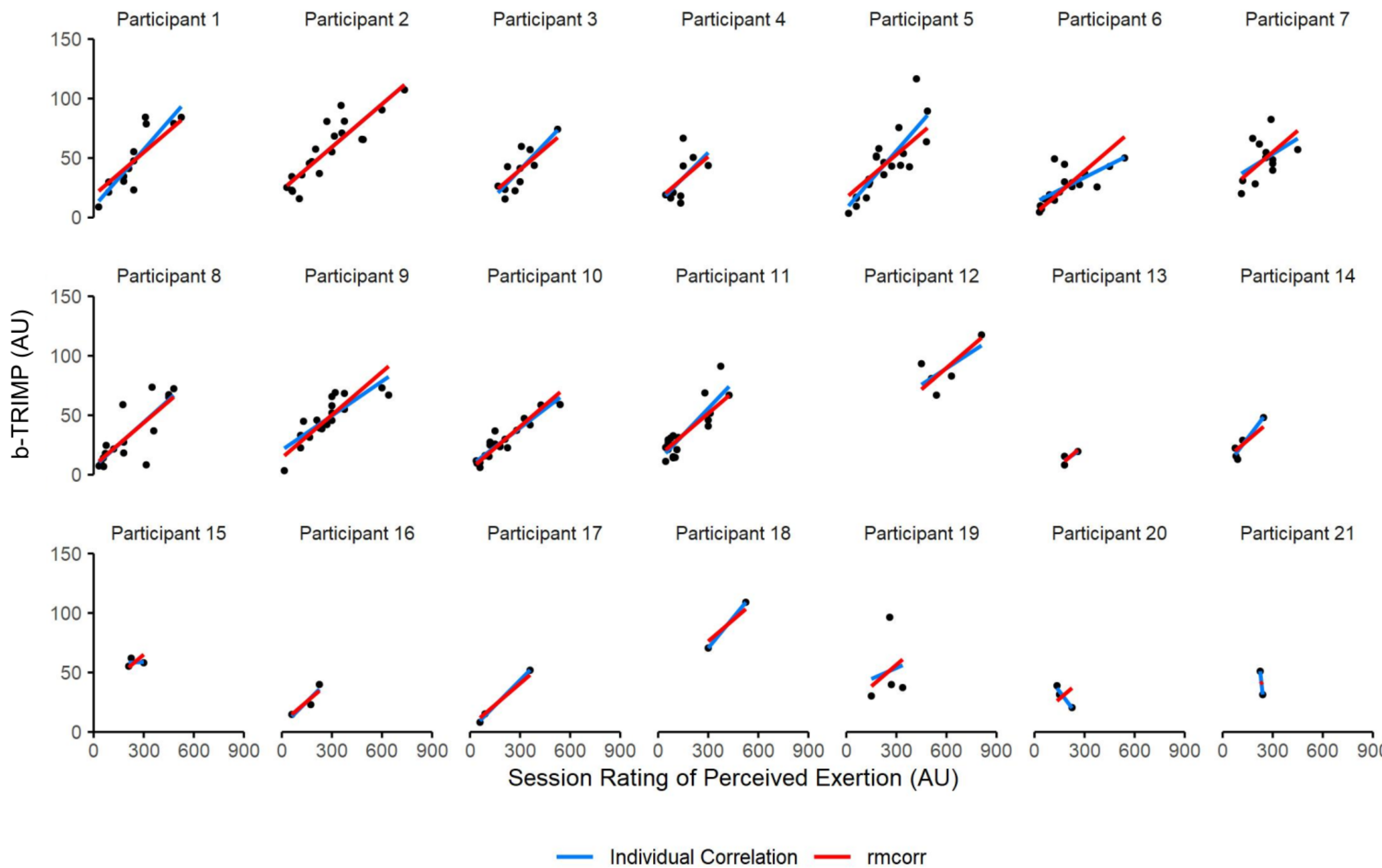


Figure 6.3: A comparison of Pearson's correlation and repeated measures correlation results for relationships between session rating of perceived exertion and Banister training impulse (b-TRIMP). Each session completed by a participant is represented by a black circle. Blue lines depict individual Pearson's correlations for each participant. Red lines depict the goodness of the repeated measures correlation fit for each participant.

Table 6.1: Correlation coefficients, *p* values, and 95% confidence intervals for intra-individual relationships between session rating of perceived exertion, and Edwards (e-TRIMP) and Banister (b-TRIMP) training impulse values. Raw data for each participant can be found in Figure 2.

	Sex	*n*	e-TRIMP			b-TRIMP		
			r	*p*	95% CI	*r*	*p*	95% CI
P1	F	13	0.88	< .001	0.64–0.96	0.88	< .001	0.64–0.96
P2	F	20	0.88	< .001	0.72–0.95	0.88	< .001	0.72–0.95
P3	F	11	0.84	< .001	0.48–0.96	0.81	< .001	0.41–0.95
P4	F	9	0.68	.045	0.03–0.93	0.56	.113	-0.17–0.89
P5	M	21	0.85	< .001	0.66–0.94	0.83	< .001	0.62–0.93
P6	M	20	0.70	< .001	0.37–0.87	0.73	< .001	0.42–0.89
P7	M	12	0.57	.051	-0.01–0.86	0.46	.132	-0.15–0.82
P8	M	16	0.87	< .001	0.66–0.95	0.80	< .001	0.50–0.93
P9	M	20	0.83	< .001	0.61–0.93	0.83	< .001	0.61–0.93
P10	M	20	0.96	< .001	0.90–0.98	0.95	< .001	0.88–0.98
P11	M	22	0.86	< .001	0.69–0.94	0.87	< .001	0.71–0.94
Mean	-	17	0.81	-	-	0.78	-	-
SD	-	5	0.11			0.14		
Range	-	9–22	0.57–0.96	-	-	0.46–0.95	-	-

measures of training load, as well as intra-individual relationships ranging from *moderate* to *almost perfect*. Based on these results, the s-RPE method can be considered a valid measure of internal training load in professional classical ballet dancers.

Both the repeated measures and individual correlations observed between s-RPE and objective measures in the present study are slightly larger than both group (r = 0.71) [110] and individual (r = 0.72 ± 0.13) [109] correlation coefficients reported in pre-professional contemporary dancers. Classical ballet and contemporary dance differ in their frequency of jumps (4.99 ± 4.93 vs. 1.71 ± 2.21 jumps per min), lifts (0.97 ± 2.53 vs. 0.12 ± 0.23 lifts per min), and changes of direction (3.34 ± 1.89 vs. 0.58 ± 0.58 changes of direction per min) [46]. Additionally, classical ballet is more intermittent, consisting of periods of higher intensity activity and longer durations of rest, subsequently incurring a significant anaerobic stress [46]. The perception of effort has previously been shown to be elevated during intermittent exercise compared with steady-state exercise of an equivalent internal load [224, 225]. The stronger relationships observed in the present study compared with previous research in contemporary dancers would, therefore, not appear to be a result of the difference in genre. An alternative explanation would be that the *very large* relationships we report could be explained, in part, by the difference in training history between cohorts. In support of this, research in swimmers [226] and athletes of mixed experience [227] revealed that the validity of s-RPE is proportional to athletic experience.

Consistent with both Jeffries et al. [109] and Surgenor and Wyon [110], we report weaker relationships between s-RPE and objective measures in ballet class compared with rehearsals. While each of these studies attributed this finding to the difference in dance genre (i.e., ballet class vs contemporary rehearsals), and ballet not being the participants' primary discipline, neither of these explanations explain the current results. One explanation may be that the cohort's familiarity with the structure, environment, and teachers of ballet class, compared with the more changeable nature of rehearsals, may have mediated this relationship. Factors such as the psychological demands, the individuals present, and the external environment of a session, for example, have all been proposed as influences on the relationship between physiological and perceptual stress [39]. We suggest, however, that this finding is most likely be a result of little inter-session variation; class follows a consistent structure each day, progressing in both physical and technical complexity from barre, to center, and finally *allegro*. Differences in perceived exertion are, therefore, finer and harder to distinguish. Additionally, this structure results in little variation in training load, as the duration and content of ballet class do not allow the dancer to reach particularly small or large training loads, to which Pearson correlation is sensitive (i.e., range restriction) [228]. The lack of change in repeated measures correlations when analysing rehearsals alone vs. rehearsals and ballet class (where the range restriction is not present), supports this idea. Practically speaking, s-RPE is, therefore, only less valid when attempting to distinguish between a set of relatively homogeneous ballet sessions.

While male and female classical ballet dancers jump, *plié*, and change direction at similar rates, they differ in their requirement to lift [46] and dance *en pointe*, respectively. During lifts of their partners, male dancers undertake L5/S1 compression forces in excess of 4000 N, and shear forces in excess of 500 N [229]. In this regard, elements of male roles bear a resemblance to resistance exercise, and could, therefore, be expected to result in differing perceptions of effort [230]. *Pointe* work, on the other hand, is incomparable to any other exercise modality; given the large pressures on the first and second toes, the perceived effort may be inconsistent with the dancer's HR [231]. Additionally, male and female intensity profiles differ, with females spending a larger duration performing at moderate and hard exercise intensities, and males performing very high intensity multi-jump routines closer resembling intermittent exercise [46]. Despite these differences, we report similar relationships between s-RPE and objective measures in both males and females. The s-RPE method is, therefore, a valid tool for monitoring internal training load, regardless of sex.

6.5.1 Limitations

Given the professional level of the current cohort, it was not possible to formally measure each participant's maximum HR. It is important to note that this will have resulted in less accurate measurements of objective measures of internal training load. Additionally, as the current cohort are considered elite ballet dancers, practitioners should consider that s-RPE may not demonstrate the same degree of validity in non-elite populations. Due to the novelty of this type of testing within the cohort, participants were given a large degree of control over the sessions in which data were collected. While we report measures of intensity and duration for the sessions completed within the current study, these data should, therefore, not be considered normative values for ballet class and rehearsal. The relatively small total number of sessions completed by female dancers, as well as the total number of female dancers involved must be considered when interpreting results regarding differences in sex. Finally, although s-RPE data are ordinal in nature, in the present analysis we use parametric tests which treat them as continuous data.

6.5.2 Practical Applications and Further Research

Unlike traditional measures used to assess internal training load (e.g., HR, $\dot{V}O_2$, [BLa]), the s-RPE method is a cost-effective and non-invasive means of monitoring internal training load. The high volumes of rehearsal undertaken by classical ballet dancers are well documented [5, 15], and have been linked with maladaptive responses leading to increased risk of injury and overtraining. The current results provide a means by which the daily and weekly training loads of dancers may be used to implement periodization models with the aim of optimizing health and performance. Differential s-RPEs have been used in sporting environments to understand multiple types of physical exertion, and the training stress imposed on multiple body parts [41]. Given the large number of different physical stressors involved in classical ballet (e.g., *pointe* work, jumping, lifting, etc.), the use of d-RPEs may provide additional insight into the training loads undertaken by dancers. Finally, understanding the validity of s-RPE is important for non-professional institutions (e.g., ballet schools) who may not have access to alternative measures of training load; further research is, therefore, warranted into the validity of s-RPE in these populations.

6.6 Conclusion

This study investigates the convergent validity of s-RPE with two objective measures of internal training load in professional classical ballet dancers. We demonstrate *very large* repeated measures correlations between s-RPE and the e-TRIMP and b-TRIMP methods, as well as intra-individual relationships ranging from moderate to almost perfect. Sub-analyses revealed that correlation coefficients were similar between male and female participants, however, relationships were stronger in rehearsals compared with ballet class. These results are similar to findings previously reported in both sport and dance research, and support the use of the s-RPE method as a valid and practical tool for measuring internal training load in professional classical ballet dancers.

CHAPTER 7

The Validity of an Open-Source Rule-Based Algorithm for Measuring Jump Frequency and Height in Ballet using Wearable Accelerometer Data

7.1 Abstract

Aim: To determine the validity of an open-source algorithm for measuring jump height and frequency in professional ballet using a wearable accelerometer. **Methods:** To determine the validity of the measurement of jump frequency, nine professional ballet dancers completed a routine ballet class whilst wearing an accelerometer positioned at the anterior lower abdomen. Two investigators independently conducted time-motion analysis to identify time points at which jumps occurred. Accelerometer data were cross-referenced with time-motion data to determine classification accuracy. To determine the validity of the measurement of jump height, a further five participants completed nine *jetés*, nine *sautés*, and three double *tour en l'air* from a force plate. Jump height predicted by the accelerometer algorithm was compared to the force plate measurement of jump height to determine agreement. **Results:** Across 1440 jumps observed in time-motion analysis, 1371 true positives, 34 false positives, and 69 false negatives were identified by the algorithm, resulting in a sensitivity of 0.98, a precision of 0.95, and a miss rate of 0.05. For all jump types, mean absolute error was 2.6 cm and the repeated measures correlation coefficient was 0.97. Bias was 1.2 cm and 95% limits of agreement were -4.9 to 7.2 cm. **Conclusions:** This study provides ballet companies and schools with a valid and cost-effective method of measuring jump load, which does not require data science expertise to implement. Jump load may be used to manage training loads, implement periodization strategies, or plan return-to-dance pathways for rehabilitating dancers.

7.2 Introduction

In professional ballet, jumping and landing movements are the most common mechanism of time-loss injury (27% and 38% of time-loss injuries in women and men, respectively) [163]. During a professional ballet performance, dancers jump at a rate of 4.99 ± 4.93 jumps·min^{-1}, [46] exceeding rates observed in sports such as volleyball (1.04 jumps·min^{-1}) [232] and basketball (41–56 jumps·match^{-1}) [233]. In these sports, jump load has been associated with changes in injury risk and performance [232, 234, 235]. As a result, jump load has been suggested to be 'the next great injury analytic' in sports medicine research [154]. In ballet, however, whilst jump load is increasingly recognised as an important variable, it is not yet routinely collected. The monitoring and management of jump load may, therefore, be a method by which maladaptive responses to ballet training may be attenuated [154].

The measurement of jump load has been facilitated by the development of algorithms which can identify jumping actions from wearable accelerometer signals. Several commercial wearable devices have been validated for the measurement of jump volume and intensity in athletic settings [234, 236, 237, 238]. However, financial and cultural barriers make investment in high-end wearable technology unrealistic for many ballet healthcare departments, and rarely are the details of these algorithms shared publicly. Furthermore, the majority of studies validating jump algorithms have been conducted in volleyball players [204, 238] or in non-sport-specific individuals [239]; the extent to which these results can be extrapolated to ballet is unknown.

Only one study has investigated the use of wearable sensor algorithms for activity recognition in ballet, using convolutional neural networks, and between 1–6 wearable IMUs, to identify jumps and leg lifts [114]. Though activity recognition was high with multiple sensors, and when the movements were analysed in isolation (98.0–98.5%), accuracy decreased when transition movements were introduced, and only a single sensor was used (78.0–81.6%). Furthermore, implementation of this method is impractical, given that considerable data science expertise is required, and the data and algorithms are not published open-source.

The aim of the current study was to investigate the validity of an algorithm for measuring the height and frequency of jumps in professional ballet. To maximise the ease of implementation, we used a simple rule-based algorithm requiring only one sensor, and share the algorithm in several formats.

7.3 Methods

7.3.1 Design

A cross-sectional study design was employed to investigate the validity of measuring jump frequency and height using an accelerometer and a rule-based algorithm. The investigation was comprised of two sub-studies. Firstly, the accelerometer measurement of jump frequency was validated against time-motion analysis during ballet class. Participants were nine professional ballet dancers (four men: age 25.6 ± 3.1 y; height 177.0 ± 6.0 cm; mass 70.4 ± 6.3 kg; five women: age 30.4 ± 5.4 y, height 164.4 ± 4.2 cm; mass 52.0 ± 3.2 kg). Secondly, the accelerometer measurement of jump height was validated against a force plate measurement. Participants were five male professional ballet dancers (age 24.7 ± 1.2 y; height 180.8 ± 2.5 cm; mass 73.0 ± 5.1 kg). Following a full explanation of the study protocol, participants gave written informed consent. Ethical approval was granted by the local board of ethics in accordance with the Declaration of Helsinki.

7.3.2 Materials and Measures

A nine-degrees-of-freedom (DOF) IMU (LSM9DS1, STMicroelectronics, Geneva, Switzerland), housing a three-DOF 100 Hz accelerometer was used. Participants wore a tightly fitting elasticated strap housing the device in a pouch situated at the anterior lower abdomen, such that the accelerometer axes were roughly aligned with the anatomical axes of the participant. Data were recorded to a secure digital card and uploaded following completion of each protocol.

For the reference measurement of jump height, force plates (ForceDecks FDLite, Vald Performance, Newstead, Queensland, Australia; or Kistler type 9268A, Kistler AG, Winterthur, Switzerland) placed on a concrete floor, sampling at 1000 Hz were used. For the time-motion analysis, ballet classes were filmed using a Sonycam DCR-SX33E (Sony Group Corporation, Tokyo, Japan; 640 x 480 pixels, 25 frames per second).

7.3.3 Protocol

7.3.3.1 Jump Frequency

Participants each completed one of three unaltered ballet classes, delivered as part of a normal working day at the Royal Opera House. Each participant wore an accelerometer for the full duration of class. The video camera was placed in an elevated position in a front corner of the studio. Two investigators reviewed the footage to identify timestamps at which dancers performed a jump. In line with previous research of this nature [237, 137, 46], jumping events were determined subjectively by the reviewers. To ensure accuracy, any discrepancies in time-motion analysis were settled by a third investigator. Where the view of the movement was obscured (e.g., by another dancer), the movement was excluded from the analysis. Timestamps identified through time-motion analysis were then cross-referenced with timestamps identified by the accelerometer algorithm.

7.3.3.2 Jump Height

Participants completed three sets of jumps on a force platform. Set one consisted of nine *sautés* (a two-to-two foot vertical jump), set two consisted of nine unilateral *jetés* (an anterior leap from one leg to the other), and set three consisted of three double *tour en l'air* (a two-to-two foot vertical jump with 720°). To ensure a range of jump heights were measured, *sautés* and *jetés* were manipulated through the participants' effort levels (3 × 30%, 3 × 60%, and 3 × 90% of maximum effort). Participants began each trial with a three second stationary period during which a body mass was recorded. For the *sautés* and double *tour en l'air*, participants jumped from, and landed in the same location. For the *jetés*, participants jumped anteriorly from the force plate and landed at a self-determined distance. Reference jump height was calculated from raw force-time data using the take-off velocity method detailed elsewhere [240], whereby jump height is calculated as: take-off velocity^2/2g.

7.3.4 Data Analysis

Following the completion of each protocol, data were uploaded from the accelerometer. Tri-axial acceleration data were filtered using a fourth order zero-lag low-pass Butterworth filter with a cut-off frequency of 12 Hz, and processed using a rule-based algorithm. The algorithm was hand-crafted, and created prior to this study based on data collected as part of routine monitoring at a professional ballet company between April 2019 and December 2020. A simplified overview of the steps undertaken by the algorithm can be found in Figure 7.1. Raw R code used to run the algorithm can be found in Appendix E; an R Shiny web application housing an interactive user interface is presented in Chapter 9; a Microsoft Excel spreadsheet containing the algorithm can be found in Appendix E.

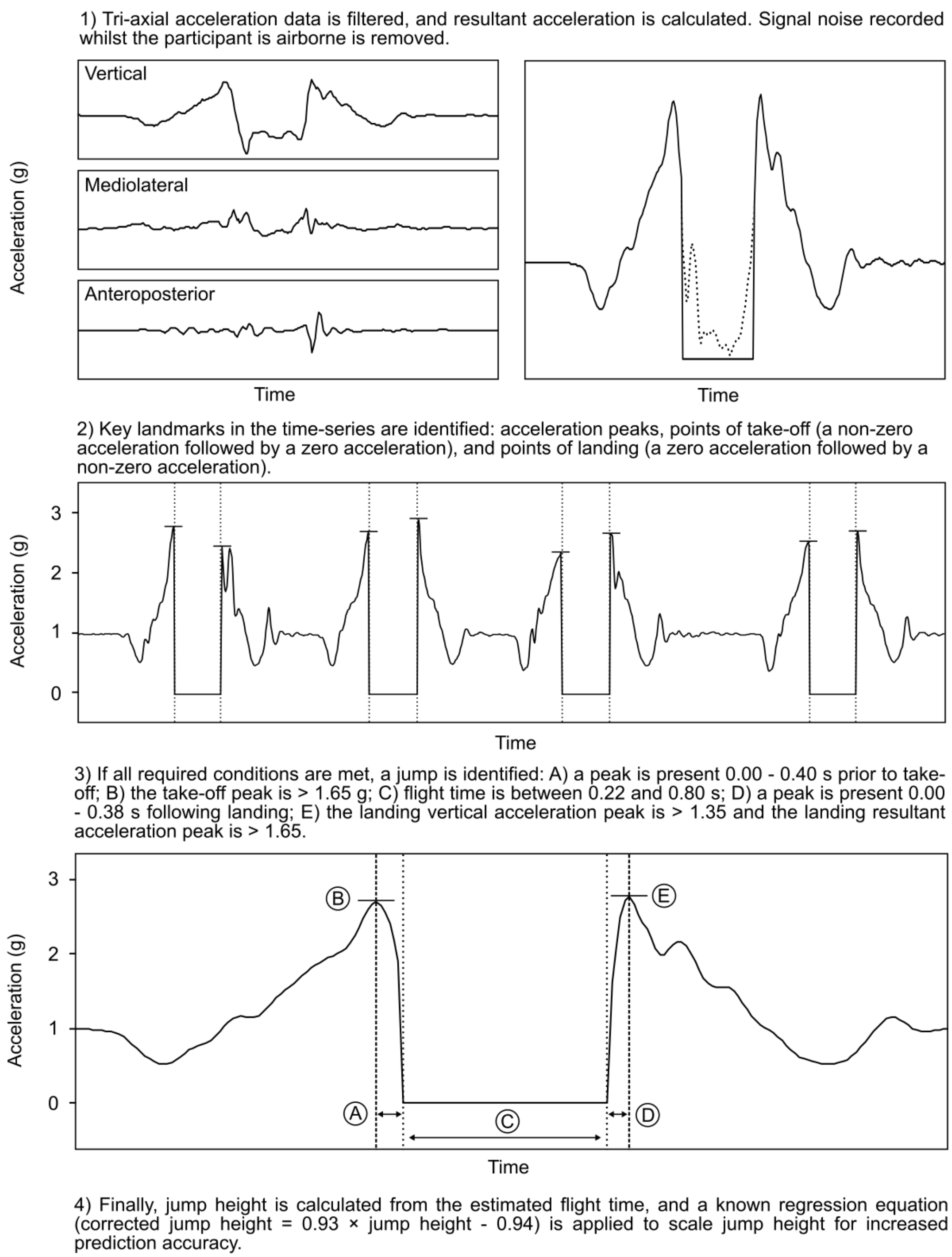


Figure 7.1: Schematic illustrating the simplified steps involved in the algorithm to identify jumps and calculate jump height.

7.3.5 Statistical Analysis

Mean absolute error (MAE), repeated-measures Bland-Altman plots, Pearson's correlations, and repeated measures correlations were used to measure the agreement and correlation between accelerometer-derived jump height and the criterion measure of jump height. For the validation of jump frequency during ballet class, the count of true positives (TP), false positives (FP), and false negatives (FN), and subsequently the sensitivity (TP / [TP + FN]), precision (TP / [TP + FP]), miss rate (FN / [FN + TP]), and critical success index (TP / [TP + FN + FP]), were calculated. Accuracy and specificity were not calculated based on the absence of a true negative measure. All analysis took place in R v.4.0.4 (R Foundation for Statistical Computing, Vienna, Austria).

7.4 Results

For the validation of jump height, a total of 105 jumps were observed (45 *sautés*, 45 *jetés*, 15 double *tour en l'air*). The MAE, Pearson's correlation, repeated measures correlation, bias, and 95% limits of agreement for the comparison of predicted jump height and reference jump height can be found in Figure 2.

For the validation of jump frequency, a total of 1440 jumps were observed. Eleven observations were removed from the study as both reviewers, or one reviewer and the third reviewer, agreed that a jump could not be reliably determined due to an obstructed view. Agreement between the two primary reviewers was 93.6%. Results and summary statistics of the IMU and video analysis are presented in Table 1.

7.5 Discussion

This study demonstrated the validity of a hand-crafted rule-based algorithm for measuring jump height and frequency in professional ballet. Unlike previous studies validating the use of wearable technology to measure jump-load, the present algorithm is open-source, does not require data science expertise, and is shared alongside R code, an R Shiny application, and an Excel spreadsheet, which can be used to facilitate implementation. This study, therefore, provides healthcare practitioners working in ballet companies and schools with a practical open-source tool for monitoring the jump load experienced by dancers.

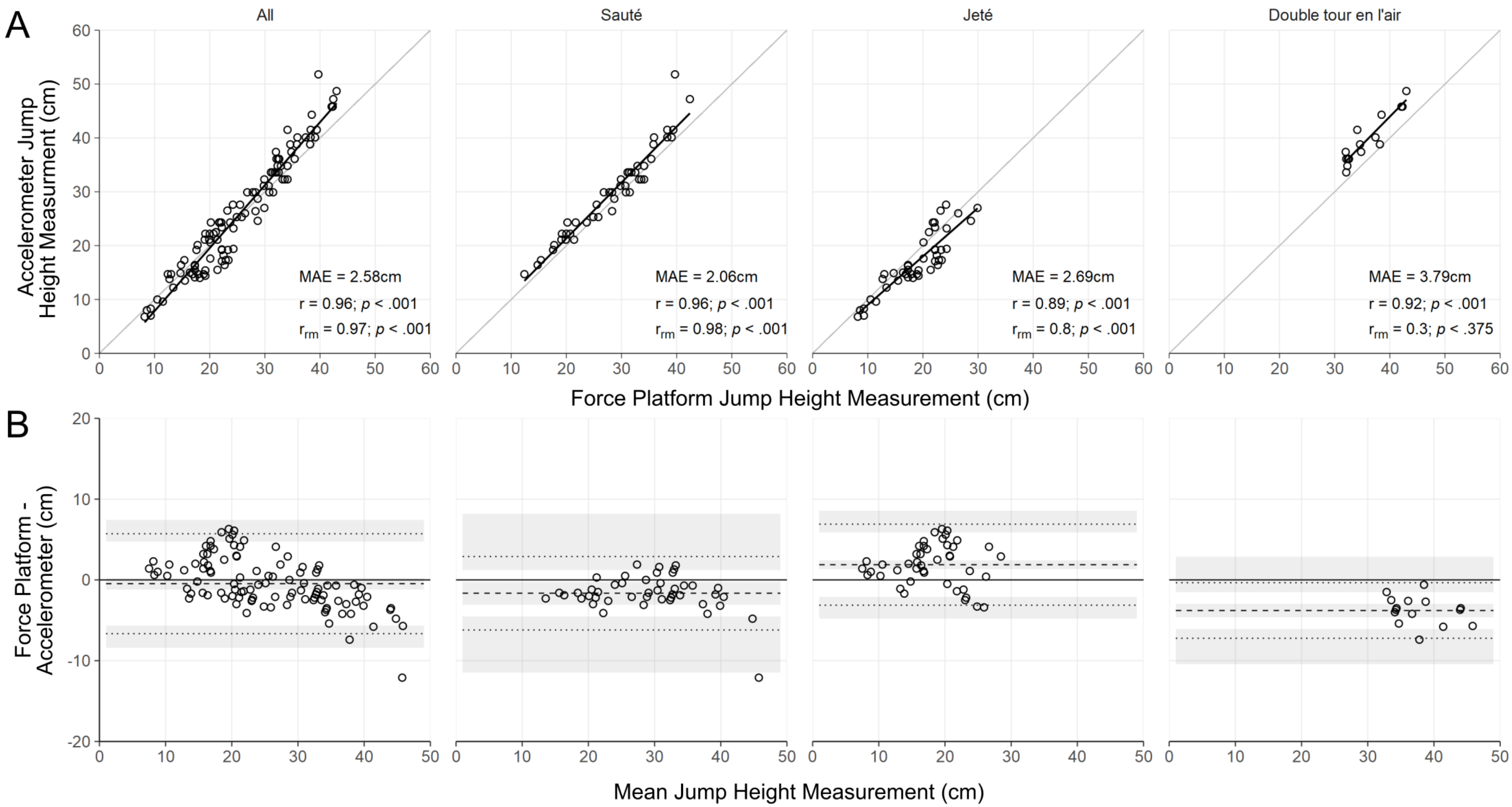


Figure 7.2: A) Correlation and B) Bland-Altman plots illustrating the relationship and agreement between accelerometer-derived and force platform-derived measurements of jump height. Grey areas represent 95% CIs for the mean bias, and upper and lower confidence intervals. MAE = Mean absolute error; r_{rm} = repeated measures correlation.

Table 7.1: Results of the cross-validation of jump frequency.

Participant	Sex	Rank	Video Count	Acc. Count	TP	FP	FN	Sensitivity	Precision	Miss Rate	CSI
1	M	A	191	196	187	7	4	0.98	0.96	0.02	0.94
2	M	FA	200	201	188	11	12	0.94	0.94	0.06	0.89
3	M	FS	211	207	204	3	7	0.97	0.99	0.03	0.95
4	M	P	242	243	232	7	10	0.96	0.97	0.04	0.93
5	F	A	103	102	101	1	2	0.98	0.99	0.02	0.97
6	F	FA	154	148	144	3	10	0.94	0.98	0.06	0.92
7	F	S	131	124	124	0	7	0.95	1.00	0.05	0.95
8	F	P	118	110	108	1	10	0.92	0.99	0.08	0.91
9	F	P	90	85	83	1	7	0.92	0.99	0.08	0.91
Combined	-	-	1440	1416	1371	34	69	0.95	0.98	0.05	0.93
Mean	-	-	169	166	161	4	8	0.95	0.98	0.05	0.93
SD	-	-	53	56	52	4	3	0.02	0.02	0.02	0.03

Acc. Count. – Accelerometer Jump Count; CSI – Critical success index; FP – False positives; FN – False negatives; TP – True positives; SD – Standard deviation; F – Female; M – Male; A – Artist; FA – First Artist; S – Soloist; FS – First Soloist; P – Principal.

The present validation of jump count revealed sensitivity, precision, and miss rate values of 0.95, 0.95, and 0.05, respectively. These values are comparable to similar studies investigating the validity of commercial wearable devices in sports such as volleyball [237, 238] and snowboarding [241], and justify the use of this algorithm in practice. Similarly, a high level of agreement was observed between the estimated jump height and the reference measure (r_{rm} = 0.97, bias = +1.2 cm, 95% LoA: -4.9 to 7.2 cm, MAE: 2.6 cm). These values are more accurate than those that have been reported in validation studies of commercial accelerometers (r = 0.91, bias = 2.5 cm, 95% LoA -6.1 to 9.8 cm [237]; bias = 9.1 cm, intra-class correlation = 0.93 [238]). Readers should note that the present algorithm appears to slightly overestimate large jumps; though this small bias is unlikely to be clinically relevant for load management, practitioners should note that the algorithm is not appropriate for the measurement of maximal jump height in isolation.

The present algorithm has several advantages over previous approaches, making its implementation into day-to-day rehearsal more practical. Firstly, only a single sensor is required to calculate jump load, which is likely to be better received by dancers than multi-sensor approaches. Additionally, a waist-worn device is easily hidden, and does not obstruct the dancer's movement. A three-DOF accelerometer—rather than a nine-DOF IMU—is used; this is advantageous both in terms of cost and signal processing requirements. The algorithm used is simpler than machine learning approaches that have been used previously [114]. This is beneficial for several reasons. Firstly, the user is not required to have data science expertise; users with only basic data handling experience can implement the algorithm using the spreadsheet contained in Appendix E. Similarly, this method is, therefore, more interpretable, and does not come in a black box, as would many machine learning models. Finally, the rule-based approach does not have the same demand for training data [114]; as a result, the data collection, training, and processing durations are considerably less.

Jump load has previously been demonstrated to be a useful metric for understanding injury risk in basketball [234] and volleyball [242]. However, whilst the present algorithm provides a valid means of measuring jump height and frequency during ballet, it is important that healthcare practitioners understand that jump load is not a direct measure of physiological tissue damage [20, 67]. Jump load may provide a means through which load can be managed (e.g., ensuring gradual progression following injury, identifying rapid increases in load), but users should be cautious not to over-rely on jump load as an injury metric, and instead consider it only one part of a larger puzzle. The ability to measure jump load provides benefits beyond injury risk management. Understanding the jumping demands experienced during rehearsals and performances may be beneficial for strength and conditioning coaches designing supplementary training programs [137] Similarly, for physiotherapists and strength and conditioning coaches involved in the rehabilitation of a dancer, understanding the demands of a given ballet may aid in the planning and management of a return-to-jumping pathway [243]. Finally, the measurement of jump load may facilitate discussions with artistic staff around load and season periodisation through objective data [108].

Whilst this algorithm was designed and tested on balletic jumps, we suggest that given the methodological steps taken by the algorithm, the results would be comparable for non-balletic jumps. There may, therefore, be considerable use for this algorithm in other sporting populations; for example, in jumping sports such as basketball or volleyball, or for managing plyometric load during more general training [244].

7.5.1 Strengths and Limitations

The key strength of this work is its accessibility: unlike previous research, the present algorithm is open-source and does not require data science expertise. Another strength is that unlike some studies of this nature [237], we have validated the measurement of jump frequency in an unaltered ballet class *in situ* (as opposed to creating an arbitrary set of movements) adding to the ecological validity of the present algorithm. A limitation of the current study is that the algorithm used does not differentiate between one-legged and twolegged take-offs and landings. Whilst this is possible using wearable technology, the aim of the present study was to provide a method requiring limited equipment (i.e., a single accelerometer) and only a basic level of data handling.

7.6 Conclusion

The present study found a rule-based algorithm to be valid for the measurement of jump height and count in professional ballet. This algorithm has been designed to increase accessibility: open-source software is provided; the algorithm does not require data science expertise to use; and only a single sensor is required. The algorithm, therefore, provides a practical method of monitoring an important external load variable in ballet. The ease of use and low-cost of applying this method provides a solution to the management of jump load in ballet companies and schools.

CHAPTER 8

Lower Limb Tissue-specific Force Prediction During Jumping and Landing Using Inertial Measurement Units and Recurrent Neural Networks

8.1 Abstract

Background: Current measures of external training load have been criticised for their failure to quantify forces at a tissue-specific level. The aim of the current study was to develop models for predicting lower-limb tissue forces from wearable IMU data during jumping and landing. **Methods:** Six male participants completed 14 sets of jumping and landing movements in a laboratory whilst wearing five six-DOF IMUs. Musculoskeletal modelling was used to calculate reference measures of Achilles tendon force, patellar tendon force, tibial force, and ground reaction force. Each force variable acted as the target for a recurrent neural network developed using IMU signals. Models were trained and evaluated using a leave-one-subject-out cross validation approach, and compared with results derived from simple shank and waist resultant acceleration linear regression approaches. **Results**: Two-IMU (waist and shank) neural networks outperformed shank and waist linear regression approaches across all tissue forces, both for continuous time series prediction (mean root-mean-square-error = 0.93 BWs, mean r^2 = 0.80) and for the prediction of peak force during each ground contact (mean root-mean-square-error = 1.48 BWs, mean r^2 = 0.58). The shank IMU linear regression approach had the worst prediction accuracy, demonstrating weak continuous time series prediction (mean root-mean-square-error = 1.56 BWs, mean r^2 = 0.26) and no peak force prediction (mean root-mean-square-error = 2.34 BWs, mean r^2 = 0.03). **Conclusions:** The current algorithms demonstrate considerable improvement over approaches using only segmental resultant acceleration. These results are promising given

the potential areas for further refinements, including modelling, hardware, and protocol. All data and code are provided, and an R application accompanies this study, providing a graphical user interface to the algorithms.

8.2 Introduction

Etiological frameworks for overuse injury risk in sport have described a balance between tissue load and tissue capacity, whereby injury occurs when tissue load exceeds tissue capacity [71, 72]. In this respect, overuse injuries can be considered a result of mechanical fatigue [67]: biomechanical load applied to a musculoskeletal tissue results in microdamage, reducing the tissue's material strength, such that failure occurs at loading magnitudes below the capacity of the tissue at full health [20, 67]. The conceptual relationship between training load and injury risk is, therefore, predicated on the biomechanical load-response pathway [20]. Recently, however, the inability of common external training load variables to accurately measure internal tissue forces has been highlighted [20, 245]. As a result, the conceptual basis of common load monitoring strategies—i.e., that wearable measures of external load are indicative of internal tissue forces, and subsequently tissue damage—is flawed until valid measurements are developed.

Jumping is the most common mechanism of injury in ballet [163], associated with 30.7% and 21.6% of all injuries in men and women, respectively. Science and medicine practitioners working in ballet—and those in sports in which jump-related injuries are common [246, 247]—have quantified external training load using wearable IMUs, measuring variables such as jump load (i.e., jump count and height [152, 232]) or peak shank acceleration (or *impact load*) [248, 249]. Whilst these variables are relatively simplistic, and are, therefore, easily interpretable and manipulatable, the extent to which they meaningfully reflect biomechanical load has been questioned [70]. Previous research in ballet has used IMUs in conjunction with more complex algorithms to quantify ground reaction forces during jumping and landing [114]. Whilst accurate estimates have been demonstrated—and ground reaction forces mark an improvement over variables such as jump load or impact load—ultimatey, ground reaction forces are not indicative of internal tissue forces [117, 250].

Recently, machine learning algorithms have been used to predict tissue-specific forces from wearable signals during treadmill running [70]. Matijevich et al. [70]. used theoretical wearable signals (i.e., laboratory measurements that could theoretically be measured using wearables) processed using LASSO regression to estimate tibial force, observing a high level of estimation accuracy (root mean square error [RMSE]: 0.25 ± 0.07 BWs). However, the extent to which the accuracy of a model developed on theoretical signals would translate into practice is unknown. Furthermore, whilst treadmill running is relatively homogeneous, during jumping activities, a greater variation of movement is evident. Therefore, there is a need to develop tissue force prediction models applicable to movements beyond running, and investigate the validity of such an approach in practice.

The aim of this study was to develop recurrent neural networks harnessing inertial measurement unit signals to estimate Achilles tendon, tibia, and patellar tendon forces— three primary sites of injury in professional ballet dancers [163]—during jumping and landing movements. These algorithms were evaluated and compared to the use of current impact loading variables used in high-performance sport: shank acceleration and waist acceleration [112, 248].

8.3 Methods

8.3.1 Participants

Participants were 6 males (25.5 ± 2.5 y, 178.6 ± 4.5 cm, 69.4 ± 5.0 kg). Prior to the onset of data collection, the full study protocol was explained to the participants and written informed consent was given. Ethical approval was given by the institutional ethics board in accordance with the Declaration of Helsinki.

8.3.2 Design

Participants completed a series of jumping trials in a biomechanics laboratory whilst wearing retroreflective markers and five IMUs. Musculoskeletal modelling was used to calculate reference measures of Achilles tendon force, patellar tendon force, tibial force, and ground reaction force. For each tissue force variable, deep learning models were developed using IMU signals. Models were trained and evaluated using a leave-one-subject-out cross validation approach, and compared with results derived from single variable shank and waist acceleration linear regression models.

8.3.3 Measures

8.3.3.1 Motion Capture

Motion capture data were collected using a 7-camera motion capture system (Vicon MX, Vicon, Oxford Metrics Group, Oxford, UK) sampling at 200 Hz. Twelve retroreflective 25 mm markers were attached directly to the skin of the participants' right legs using double-sided tape, whilst two further cluster sets, each holding three markers, were attached to the right thigh and shank using self-adhesive tape. The exact placement of each marker is detailed elsewhere [251]. Force and centre of pressure data were collected using a tri-axial force platform (Kistler 9268A) sampling at 1000 Hz.

8.3.3.2 Inertial Measurement Units

Five six-DOF IMUs sampling at 100 Hz (LSM9DS1, STMicroelectronics, Geneva, Switzerland), each housing a tri-axial accelerometer and gyroscope, were used in this study. The IMUs were secured to the superior aspect of the right midfoot ('foot'); the right shank, medial to the tibial tuberosity ('shank'); the lateral aspect of the right thigh, mid-way between the greater trochanter and lateral femoral epicondyle ('thigh'); the anterior abdomen, level with the anterior superior iliac spine ('waist'); and between the scapulae, approximately level with the fifth thoracic vertebra ('upper-back'). The foot, shank, and thigh IMUs were secured to the segment using adhesive tape; the waist IMU was secured using a tightly fitting elasticated strap; the upper-back IMU was housed in a tightly fitting vest. The positioning and orientation of each IMU is detailed in Figure 8.1.

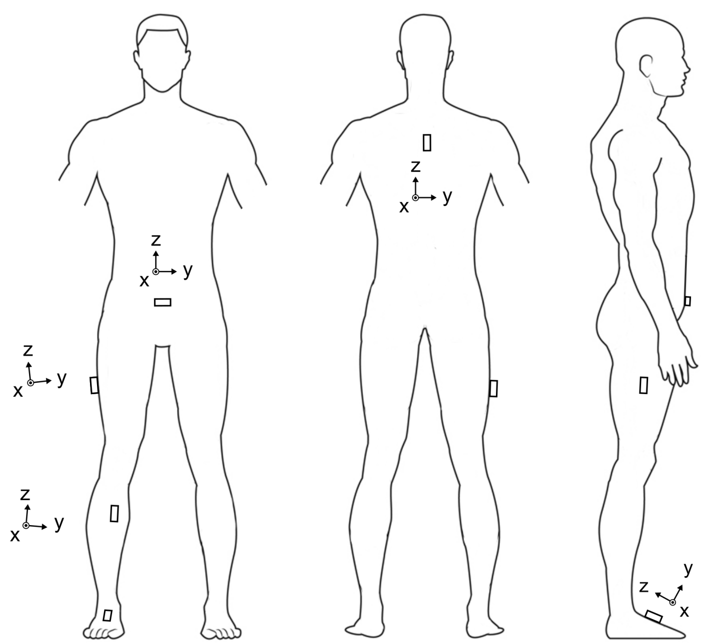


Figure 8.1: Inertial measurement unit locations and orientations.

8.3.4 Protocol

Following the completion of a standardised warm-up, participants completed 18 jumping trials, detailed in Table 8.1. To ensure a range of movement intensities, participants were directed to complete sets at either 30, 60, or 100% of maximal intensity. The full protocol included a total of 174 ground contacts for each participant.

8.3.5 Data Processing

Following the completion of data collection, motion capture data were reconstructed and labelled using Vicon Nexus software (Vicon Motion Systems Ltd, Oxford, United Kingdom), with gaps of ten frames or less interpolated using cubic splines. Motion capture data were filtered using a zero-phase 4th order low-pass Butterworth filter with a 12 Hz cut-off frequency, determined via a residual analysis. Force data were downsampled to 200 Hz prior to musculoskeletal modelling. Internal tissue forces were then calculated using the *FreeBody* model (v.2.1) [251]. *FreeBody* is a segment-based lower-limb musculoskeletal model of 5 segments, 163 muscles, and 14 ligaments, and has been validated for use in jumping movements [251]. Target variables extracted from the model were Achilles tendon force, patellar tendon force, and resultant ankle joint reaction force (as a surrogate measure of tibial force [70]). Resultant ground reaction force was extracted directly from Vicon Nexus and included as a fourth target variable [252, 253].

IMU data were uploaded, and raw linear acceleration data were filtered using a zero-phase 4th order low-pass Butterworth filter with a 22 Hz cut-off frequency. Pilot research showed that a 22 Hz cut-off frequency resulted in the greatest agreement between IMU-measured acceleration and Vicon-measured acceleration. Variables extracted from the IMU data were: tri-axial linear acceleration, tri-axial angular velocity and tri-axial angular acceleration (calculated as the 1st derivative of angular velocity with respect to time) measured in the local frame, and resultant linear acceleration, resultant angular velocity and resultant angular acceleration. Internal tissue force and IMU data were synchronised against a single 'master' IMU. All wearable IMUs were synchronised with the master IMU at the onset of each data collection session using a series of common movements, prior to attachment to the participant. The master IMU was secured to the force platform, and at the onset of each trial was tapped by the participant three times, providing time series landmarks in the ground reaction force and master IMU time series, through which musculoskeletal modelling and wearable IMU data could be synchronized. Each trial was manually inspected to ensure accurate synchronisation. Training data were scaled, normalised, and to ensure the model did not bias specific jump types or intensities, resampled with replacement to attain

Table 8.1: Descriptions of jumping and landing movements completed in each set.

Trial	Reference	Jump Type	Effort	Repetitions	Ground Contacts	Description
1	01-01	Repeated squat jump	30%	10	11	Repeated jumps performed with self-determined flexion at the hip, knee, and ankle.
2	01-02		60%	10	11	
3	01-03		100%	5	6	
4	02-01	Repeated stiff-ankle pogo jump	30%	10	11	Repeated jumps performed with a stiff ankle position and minimal flexion at the knee and hip. The participant aims to minimise ground contact time.
5	02-02		60%	10	11	
6	02-03		100%	5	6	
7	03-01	Isolated counter movement jump	30%	10	20	Individual countermovement jumps, between each of which the participant pauses and resets to their original static position.
8	03-02		60%	10	20	
9	03-03		100%	5	10	
10	04-01	Two-footed broad jump (takeoff)	30%	3	3	Two footed jumps with anterior displacement, taking off from the force plate.
11	04-01		60%	3	3	
12	04-01		100%	3	3	
13	04-02	Two-footed broad jump (landing)	30%	3	3	Two footed jumps with anterior displacement, landing on the force plate.
14	04-02		60%	3	3	
15	04-02		100%	3	3	
16	05-01	One-to-two leg vertical leap	30%	10	20	A single step into a vertical leap, following which the participant lands on two legs.
17	05-02		60%	10	20	
18	05-03		100%	5	10	

an even distribution of force magnitudes, and an even number of unilateral and bilateral jumps. All tissue force and IMU data collected in the study are provided in Appendix E.

8.3.6 Model Training and Evaluation

A leave-one-subject-out cross validation approach was used to train and evaluate a two-IMU (waist and shank IMUs) and a five-IMU (foot, shank, thigh, waist, and upper-back IMUs) prediction model, and a shank IMU and waist IMU linear regression model for each of the four targets (Achilles tendon force, patellar tendon force, tibial force, and ground reaction force). This approach involved training each model on five participants' data, and testing the model on the sixth. This process was then iterated until each participant's data had acted as the testing set. Five percent of the data set was excluded from training and testing prior to this process, and used to tune the model. Parameters tuned were the number of layers, the number of neurons in each layer, the learning rate, dropout, window size, and the window delay. For each leave-one-subject-out iteration, 25% of the data was used as a validation set.

Recurrent neural networks were built, allowing the network to access historical data points in addition to the frame being predicted. Initial model architecture was based on approaches to similar problems [254], though less complex models were used following tuning. Models consisted of a 64 neuron long short-term memory layer with 40% recurrent dropout, and two dense layers comprised of 32 and 16 neurons. Models were trained using the Adam optimization algorithm [255], a mean square error loss function, and learning rates of 1×10^{-5} or 1×10^{-6}. Training continued until the mean square error failed to decrease by 0.0001 × body mass after 15 consecutive epoch, up to a maximum of 400 epochs. Models were constructed and evaluated in R (v.4.0.4, R Foundation for Statistical Computing, Vienna, Austria) using Keras, an interface for the Tensorflow (v.2.6.0) Python library. The complete data set passed to prediction models can be found in Appendix 2. Code to recreate the models can be found in Appendix 3.

For comparison to current wearable technology approaches to load quantification, a single variable linear regression method was used [117, 70]. Linear regression models were built to calculate coefficients with which to scale the resultant acceleration measured by either the shank or waist IMU to the target variable. The resulting regression equation was then applied to the testing data to make tissue force predictions.

Models were evaluated in two ways: i) continuous time series prediction, (i.e., based on every data point recorded) and ii) peak force prediction (i.e., based on the peak forces measured during each ground contact). For each model, intra-individual root-mean-square-errors (RMSE) and Pearson's correlations were calculated for continuous time series and peak forces, to determine relationships between predicted and actual values. All model building and evaluation procedures were conducted using R.

8.4 Results

A total of 110 trials were recorded (18 trials for five participants, and 20 trials in one participants, as two trials were divided into two sections). Five trials (4.5%) were removed due to excessive marker dropout or processing errors. A total of 1042 unique ground contacts and 74096 individual data points were, therefore, included in the final analysis.

Across all tissue targets, and for both continuous time-series and peak force predictions, the leave-one-subject-out cross validation revealed that neural networks demonstrated lower RMSEs (Tables 8.2 & 8.3) and higher coefficients of determination (Figure 8.2) than waist or shank linear regression approaches. Scatter plots presenting the relationships between laboratory force measures and IMU force measures for each participant are presented in Figures 8.3–8.8.

Table 8.2: Root-mean-square-errors (RMSE) for continuous time series predicted by each algorithm compared to the laboratory measurement for each participant.

Target	Participant	RMSE for Continuous Time Series Predictions (x body mass)			
		NN-5	NN-2	Waist	Shank
Achilles Tendon	1	1.11	1.19	1.30	1.68
	2	0.88	0.85	1.07	1.46
	3	0.84	0.88	0.80	1.61
	4	1.15	0.88	0.92	1.33
	5	0.80	0.95	0.78	1.17
	6	0.85	0.85	1.08	1.41
	Mean	0.95	0.95	0.97	1.45
	SD	0.15	0.13	0.20	0.18
Patellar Tendon	1	1.04	0.97	1.09	1.58
	2	0.72	0.80	1.00	1.32
	3	0.90	0.83	0.91	1.38
	4	0.83	0.60	1.10	1.69
	5	0.93	0.96	1.10	1.54
	6	0.61	0.70	1.11	1.40
	Mean	0.84	0.81	1.05	1.49
	SD	0.15	0.14	0.08	0.14
Tibia	1	1.13	1.21	1.49	1.91
	2	0.84	0.99	1.26	1.73
	3	0.85	1.00	1.15	1.95
	4	1.15	0.92	1.12	1.64
	5	0.84	1.07	1.02	1.45
	6	0.81	0.97	1.37	1.78
	Mean	0.94	1.03	1.24	1.74
	SD	0.16	0.10	0.17	0.18
GRF	1	0.32	0.35	0.38	0.47
	2	0.23	0.19	0.32	0.41
	3	0.21	0.24	0.34	0.49
	4	0.27	0.20	0.32	0.45
	5	0.23	0.20	0.29	0.41
	6	0.21	0.23	0.36	0.44
	Mean	0.24	0.23	0.33	0.44
	SD	0.04	0.06	0.03	0.03

NN-5 – Five IMU neural network; NN-2 – Two IMU neural network.

Table 8.3: Root-mean-square-errors (RMSE) for the peak force predicted by each algorithm compared to the laboratory measurement for each participant.

Target	Participant	RMSE for Peak Force Predictions (x body mass)			
		NN-5	NN-2	Waist	Shank
Achilles Tendon	1	1.51	1.67	2.21	2.35
	2	1.24	1.17	1.90	2.47
	3	1.31	1.40	1.09	2.06
	4	2.21	1.28	1.84	2.27
	5	1.34	2.10	1.57	2.27
	6	1.64	1.37	2.21	2.40
	Mean	1.52	1.53	1.72	2.29
	SD	0.36	0.34	0.43	0.14
Patellar Tendon	1	1.06	0.94	2.23	2.35
	2	1.36	1.80	2.10	1.36
	3	1.54	1.66	1.59	1.33
	4	1.66	1.12	2.03	2.27
	5	1.65	1.27	2.19	2.10
	6	1.02	1.15	2.61	1.77
	Mean	1.38	1.32	2.12	1.87
	SD	0.29	0.33	0.33	0.45
Tibia	1	1.29	1.21	2.49	2.62
	2	1.52	1.57	2.31	3.05
	3	1.54	1.24	1.69	2.44
	4	2.28	1.23	2.19	2.73
	5	1.58	2.51	2.15	3.01
	6	1.49	1.73	2.77	3.30
	Mean	1.62	1.58	2.27	2.86
	SD	0.34	0.50	0.36	0.32
GRF	1	0.51	0.55	0.57	0.62
	2	0.34	0.34	0.55	0.57
	3	0.29	0.31	0.52	0.63
	4	0.39	0.32	0.57	0.62
	5	0.31	0.29	0.55	0.66
	6	0.30	0.35	0.70	0.74
	Mean	0.36	0.36	0.58	0.64
	SD	0.09	0.10	0.06	0.06

NN-5 – Five IMU neural network; NN-2 – Two IMU neural network.

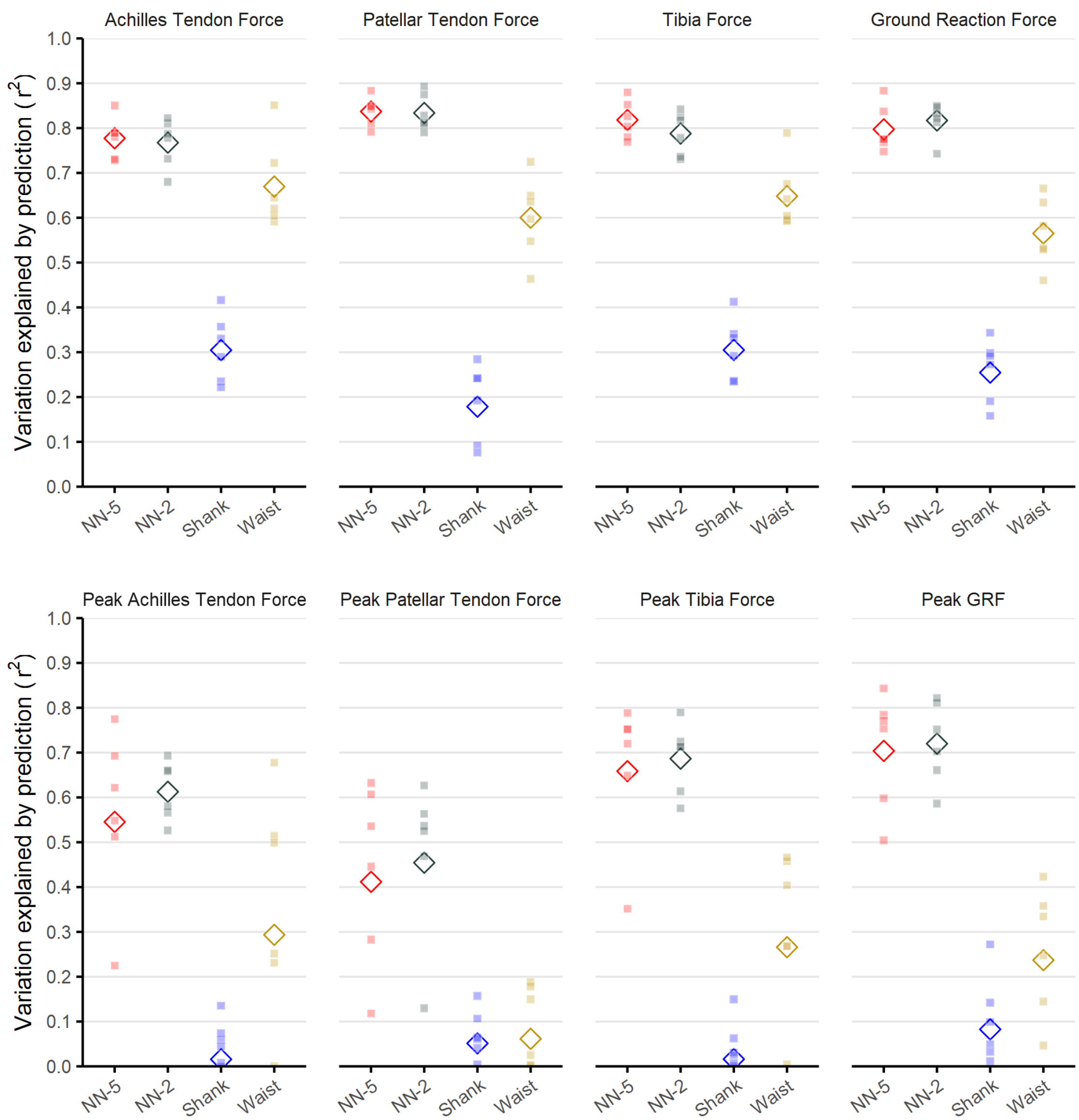


Figure 8.2: Comparisons of r^2 values for the relationships between predicted and actual force values. The upper row presents the results of continuous time series prediction, whilst the lower row presents the results of peak force prediction. Filled squares show the result of each participant, whilst diamonds show the group mean. GRF – Ground reaction force; NN-5 – Five IMU neural network; NN-2 – Two IMU neural network.

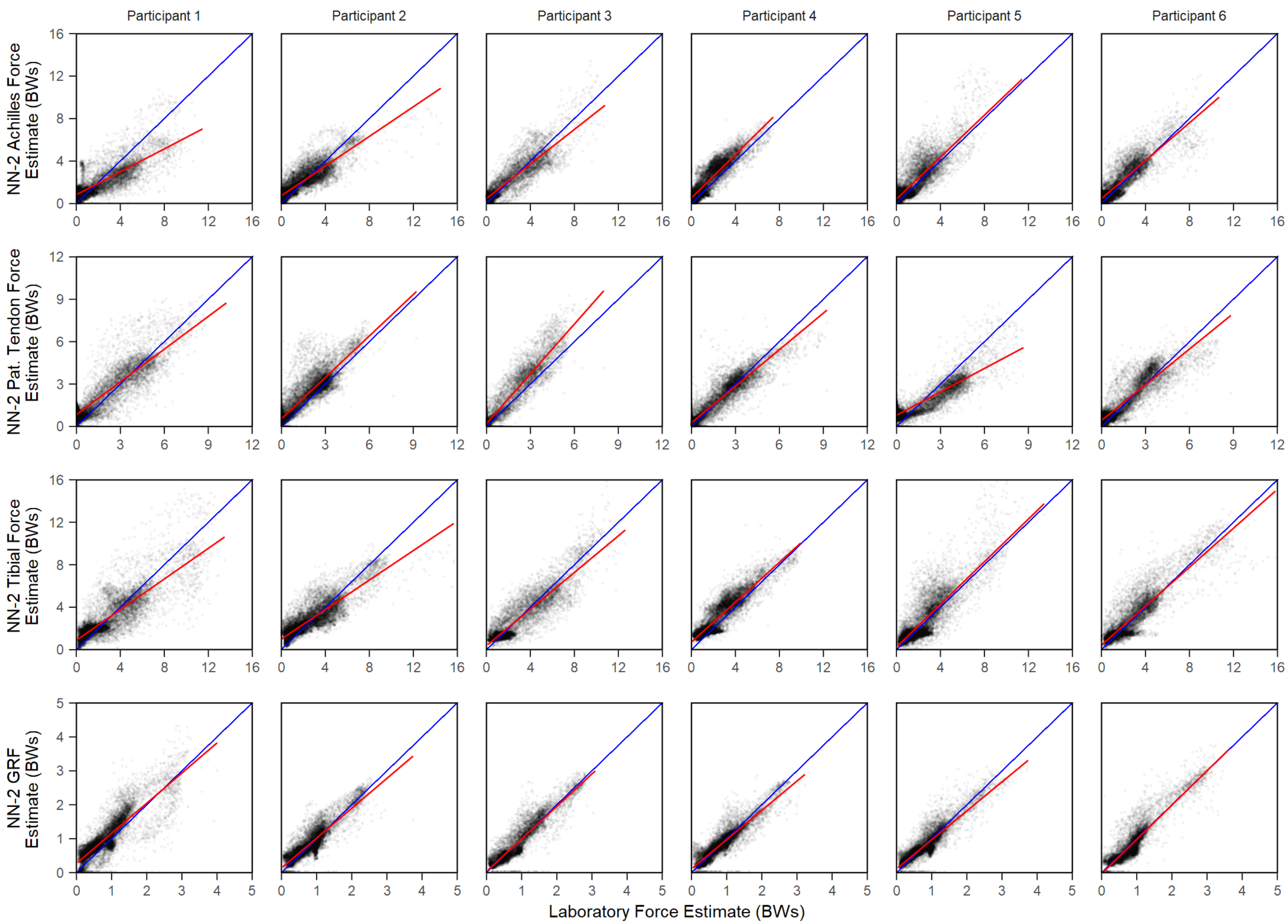


Figure 8.3: Laboratory-measurements vs. two-IMU neural network (NN-2) predictions of continuous time-series. Columns present the data of a single participant, whilst rows present each target variable.

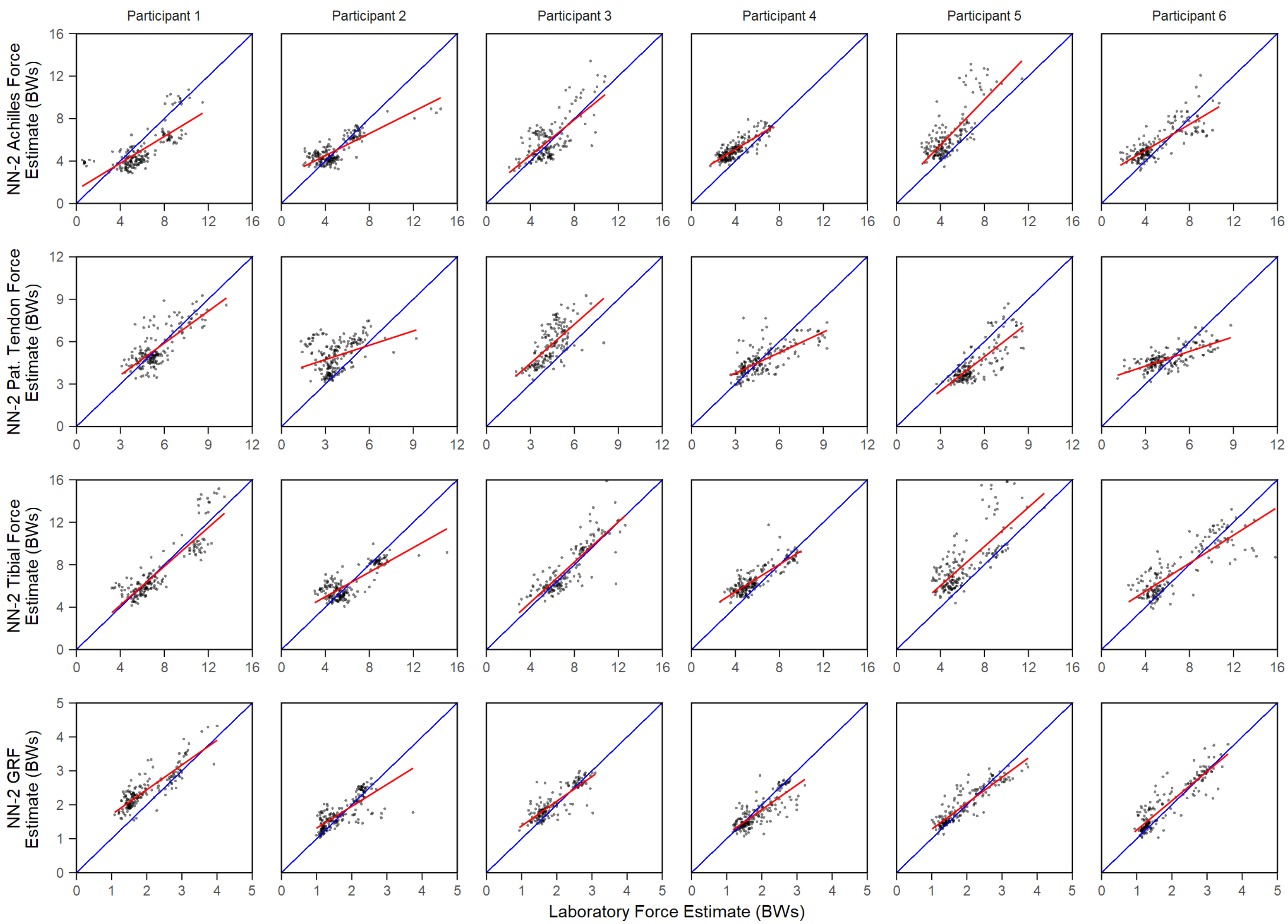


Figure 8.4: Laboratory-measurements vs. two-IMU neural network (NN-2) predictions of the peak force occurring in each ground contact. Columns present the data of a single participant, whilst rows present each target variable.

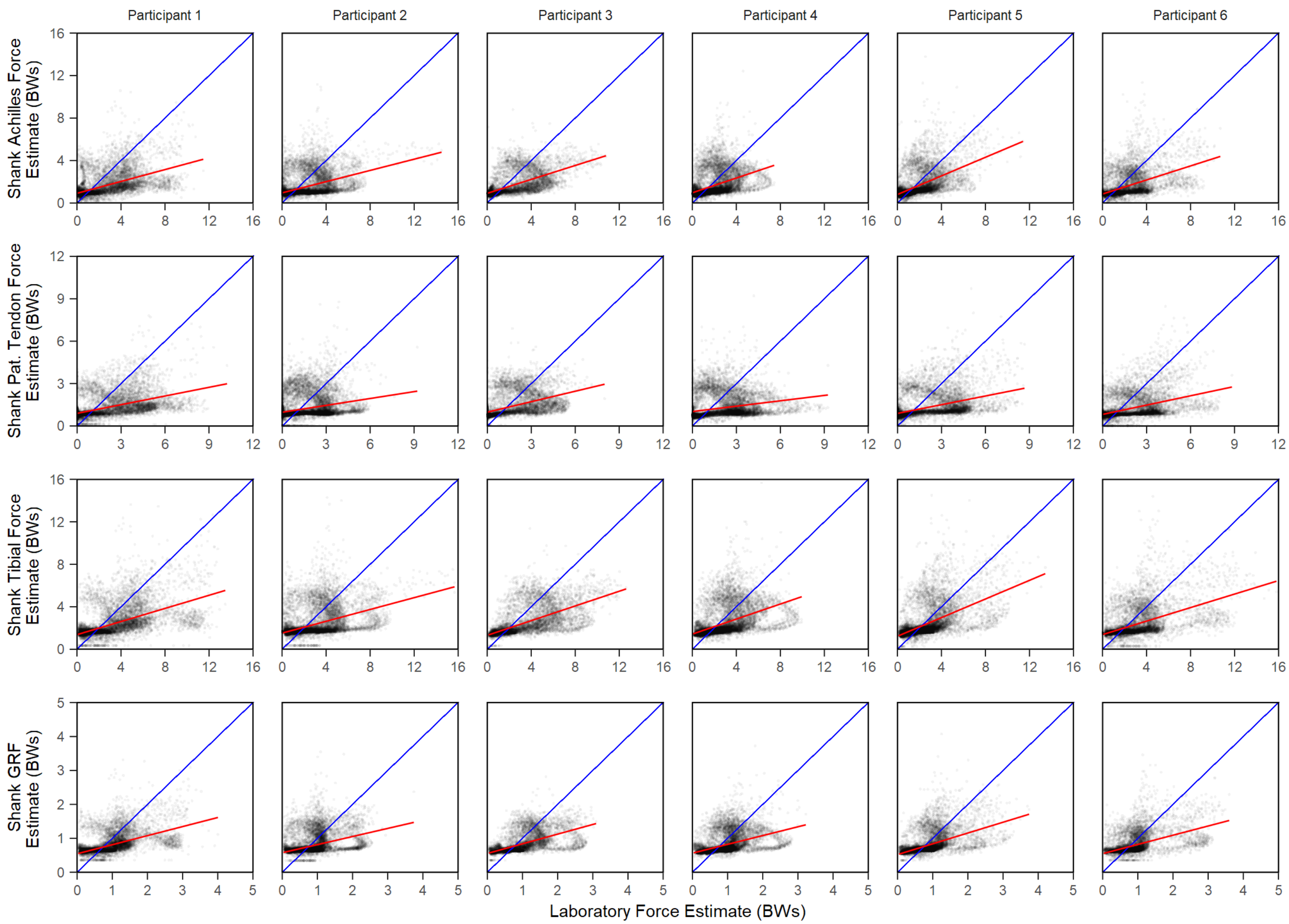


Figure 8.5: Laboratory-measurements vs. shank linear regression predictions of continuous time-series. Columns present the data of a single participant, whilst rows present each target variable.

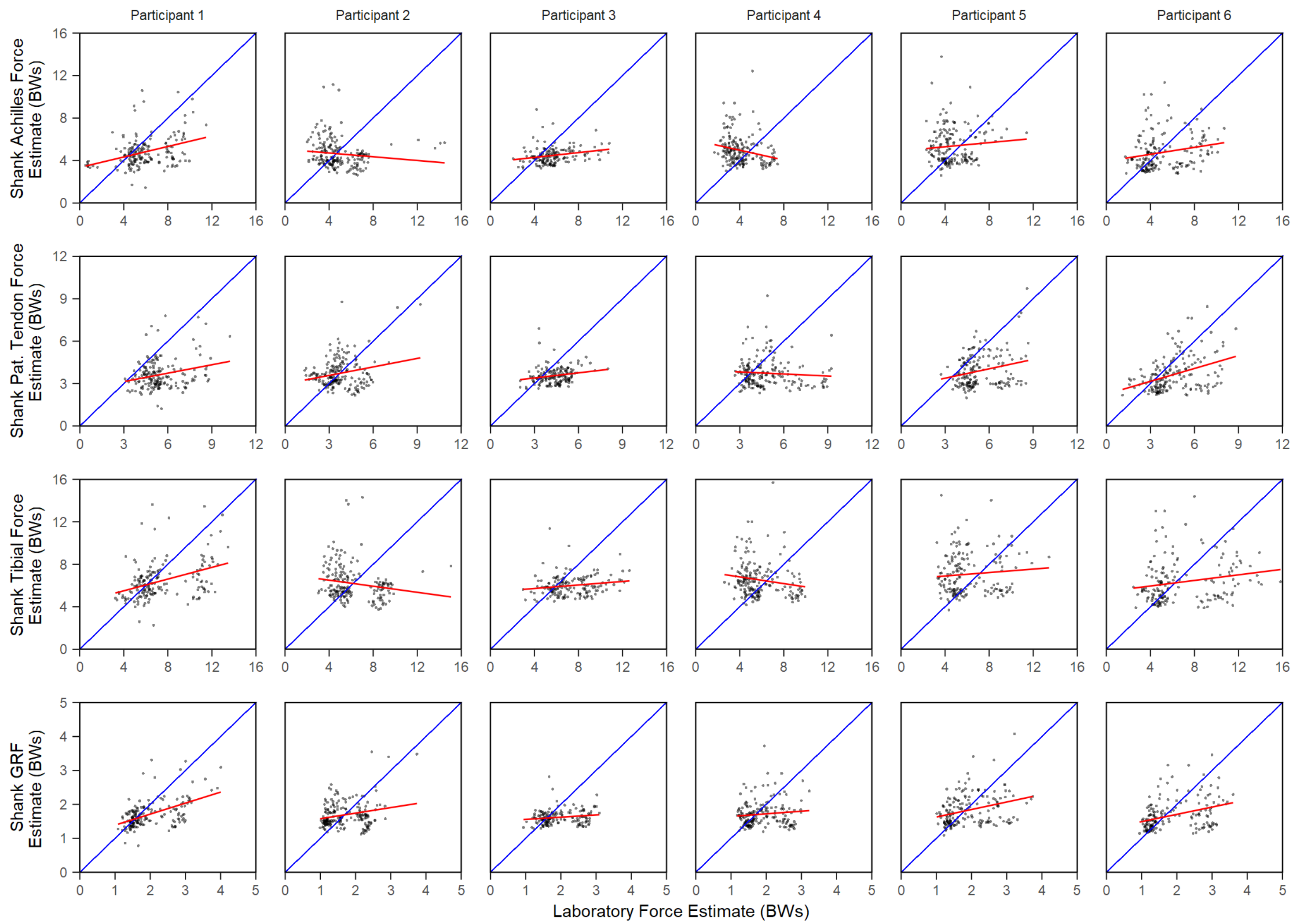


Figure 8.6: Laboratory-measurements vs. shank linear regression predictions of the peak force occurring in each ground contact. Columns present the data of a single participant, whilst rows present each target variable.

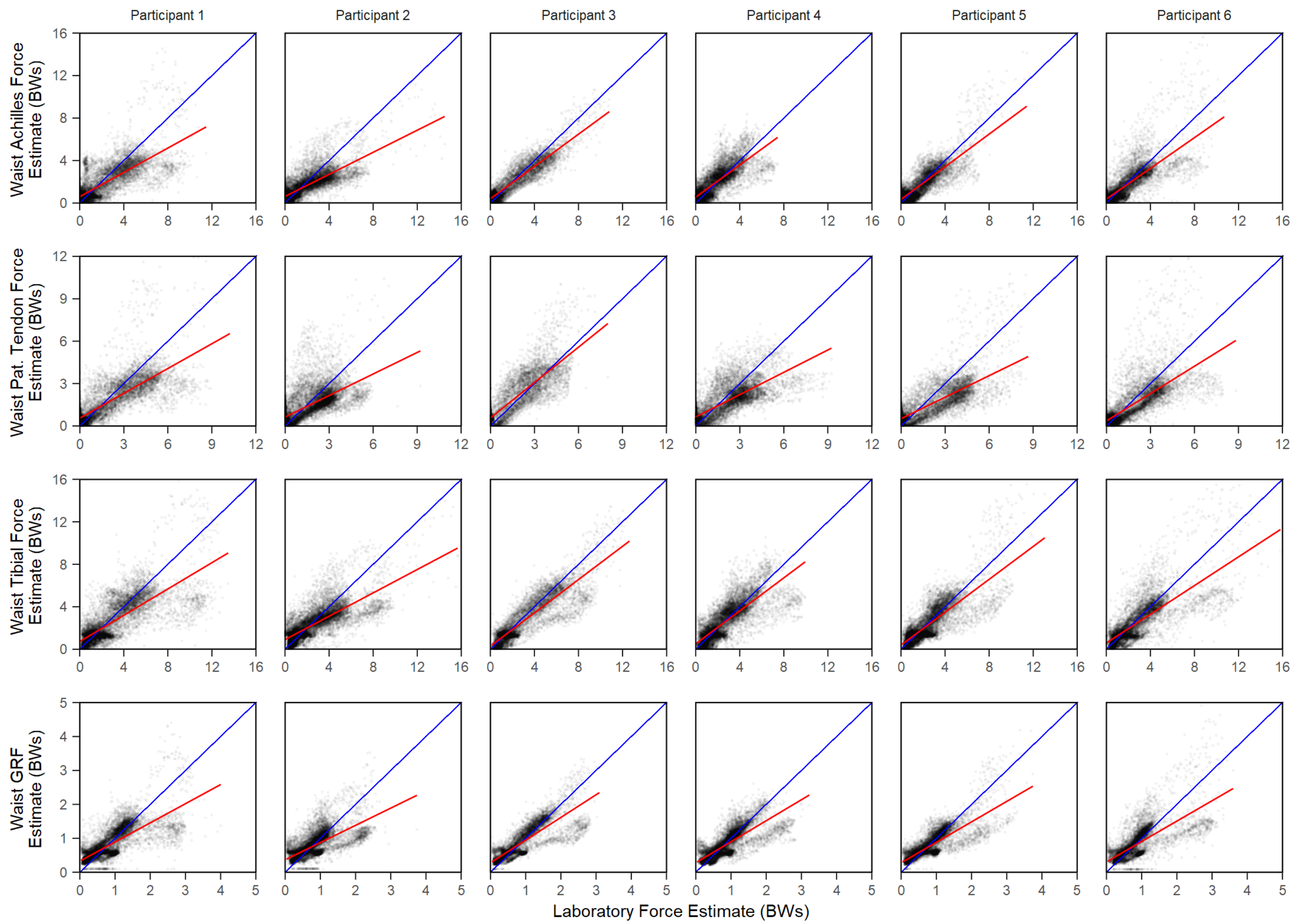


Figure 8.7: Laboratory-measurements vs. waist linear regression predictions of continuous time-series. Columns present the data of a single participant, whilst rows present each target variable.

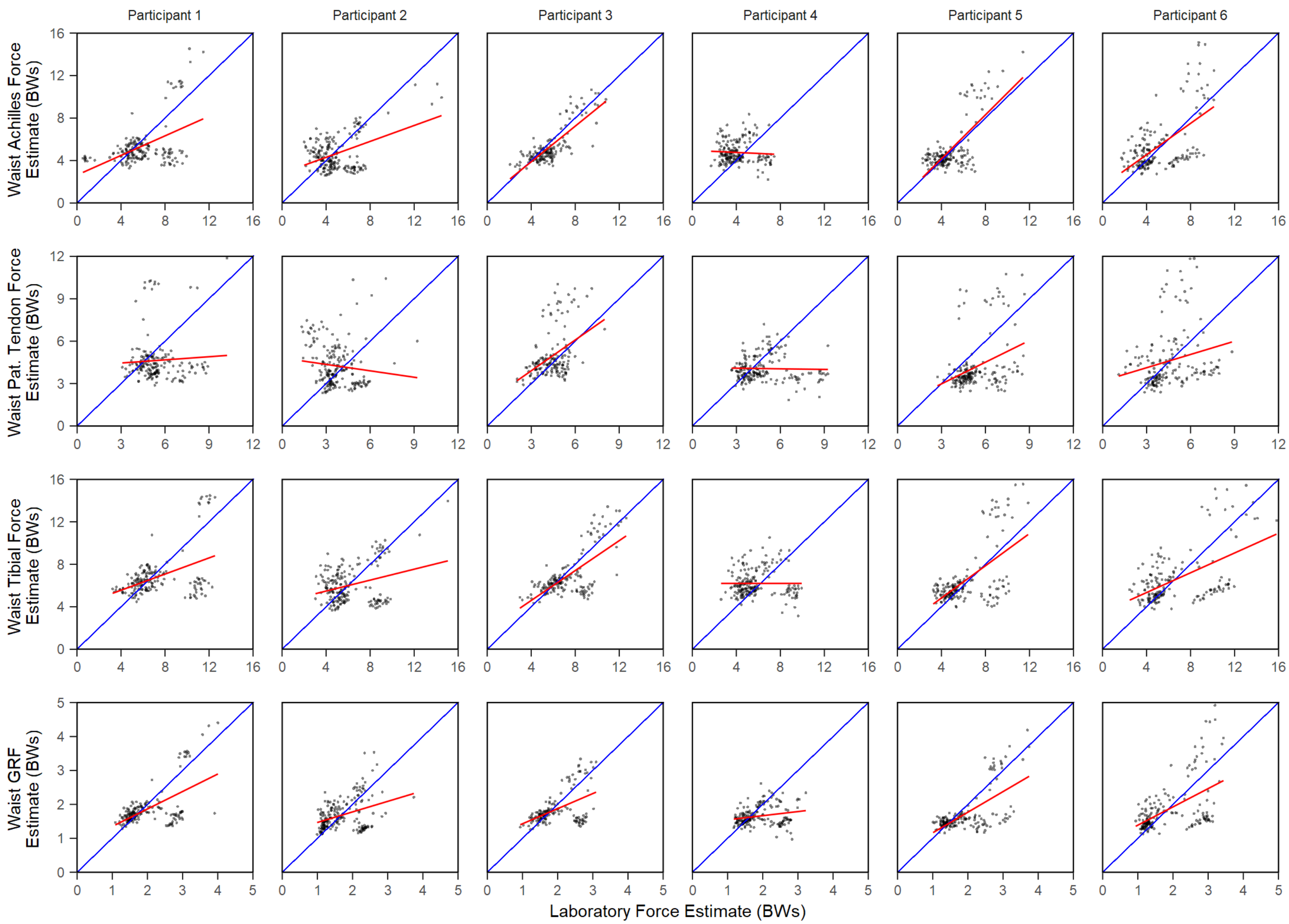


Figure 8.8: Laboratory-measurements vs. waist linear regression predictions of the peak force occurring in each ground contact. Columns present the data of a single participant, whilst rows present each target variable.

8.5 Discussion

This study presents a series of algorithms for estimating lower limb tissue forces from wearable IMU data during jumping movements, providing an improvement in field-based biomechanical load monitoring technology compared to current alternatives. These algorithms outperformed shank and waist mounted IMU measurements of lower limb tissue force considerably; indeed, simple segmental acceleration measures demonstrated such poor relationships with lower limb tissue forces that their use in future practice and research should be questioned. An open-source R Shiny application housing these algorithms, as well as the data and code used to produce them, are provided in Chapter 9. The improved accuracy observed using these novel methods may facilitate improved training load management in ballet—particularly during rehabilitation—and may extend to jumping sports such as volleyball and basketball.

In the present study, two-IMU neural network estimates of tissue-specific forces demonstrated strong relationships with musculoskeletal model measurements, for both the continuous time series (r^2 = 0.77–0.83; RMSE = 0.81–1.03 BWs) and the peak force measured during each ground contact (r^2 = 0.45–0.72; RMSE = 1.32–1.58 BWs). Estimates of peak tibial force (RMSE = 1.58 BWs) were less accurate than those observed in similar research (0.25 BWs) [70], though this is unsurprising for several reasons, namely: the use of actual vs. idealised signals, the lack of pressure sensing insoles, the use of six-DOF rather than nine-DOF IMUs, and the inclusion of more varied movements. Additionally, the current method predicted a continuous time series, before extracting the peak value. Conversely, the model of Matijevich et al. [70] targeted only peak values. A similar continuous time series prediction method has been used for the estimation of GRF during running, during which mean RMSEs of 0.16 ± 0.04 BW were observed [254] (compared to 0.23 BW in the present study). Unlike the present study, however, IMU summary statistics, participant characteristics, and movement characteristics (running speed and slope) were passed as features to the neural network. Given the differences in movements, models, sensors, and signals, it is challenging to directly compare results against these studies. It would seem pertinent, however, for future models to target the specific variable of interest (i.e., either a continuous time series or the peak value, and not both concurrently).

The neural network approach outperformed both the waist and the shank linear regression methods across all target variables. In the case of the shank IMU linear regression approach, the peak resultant acceleration measured during a ground contact explained less than five percent of the variation in the laboratory measurements of any target tissue force. This result may be surprising, given that lower-limb mounted IMUs are often suggested to be indicative of lower-limb biomechanical load [256], and are widely used during routine monitoring or rehabilitation in high-performance sport [248, 249]. However, this finding is consistent with several previous suggestions regarding the theoretical relationship—or lack thereof—between segmental acceleration and tissue force [117]. Based on the present findings, and previous findings in runners [70], shank acceleration appears to be an invalid measure of lower-limb biomechanical load during athletic movements. Importantly, these results are promising for the future of wearable technology as a means of measuring lower-limb load—however, researchers and organisations developing the technology must look beyond simple segmental acceleration.

8.5.1 Areas for Further Research and Development

Potential avenues for improvements in prediction accuracy can be broadly divided into three areas: hardware, modelling, and methodology. Firstly, additional or alternative hardware may facilitate the measurement of the measurement of further useful signals, namely IMU orientation (and by extension, limb orientation) through nine-DOF IMUs, and ground reaction force through pressure sensing insoles [257]. Although the IMU situated near the participant's centre of mass gives a reasonable proxy measure of ground reaction force, pressure sensing insoles would provide this signal unilaterally. With the addition of these more complex signals, however, comes a reduction in the ease of application of any wearable system in practice. Secondly, alternative approaches to model selection, architecture, and development may benefit prediction accuracy. Potential examples of where further improvements could be made are model type (e.g., RNNs [254], LASSO regression [70]); ensemble methods (i.e., combining several models) [258, 259]; target-specific models (i.e., models targeting peak force, rather than extracting the peak force identified from a continuous time series prediction) [70]; feature selection [260]; and additional parameter and hyperparameter tuning. Finally, methodological changes may yield improvements in an algorithm. The most notable of these would be the development of participant-specific models (i.e., models which are trained and tested on two data sets from the same participant) [261].

8.5.2 Limitations

Despite the improvement in tissue-specific force measurements observed in the present study, several limitations exist. Methodologically, future protocols should include an even number of unilateral and bilateral jumps. Whilst training data were resampled to ensure an even distribution of unilateral and bilateral jumps, the same was not the case for testing data.

As such, an algorithm which does not distinguish between the two would not have been penalized as heavily as perhaps it should. A greater sample size would be desirable, however, given the time-intensive nature of motion capture collection, musculoskeletal modelling, and algorithm development and training, large teams of researchers with state-of-the-art equipment are required for optimal outcomes. Finally, readers should consider that the criterion measures were derived from musculoskeletal modelling, and are not direct measures of tissue load. Whilst the model used has been validated for use in jumping, it makes assumptions regarding factors such as anatomical scaling and muscle dynamics [251], though these limitations are common across modelling approaches.

8.5.3 Practical Applications

Whilst it is natural to consider the application of the current findings to injury prediction/prevention, further refinement is necessary before such algorithms are sufficient to provide accurate insight into internal tissue damage in practice. This primarily stems from the non-linear relationship between load magnitude and tissue damage, whereby an increase in load magnitude results in a disproportionately large increase in tissue damage [67]. As a result, small errors in the estimation of load magnitude translate to large errors in the estimation of tissue damage. Although healthcare practitioners should be cautious about overstating the value of these algorithms of providing insight into injury risk, they mark a great improvement over simple linear regression approaches for quantifying lower limb loads. In this respect, the results demonstrate promising implications for future development of external training load measures; with only two six-DOF IMUs, a high proportion of variation in laboratory-measured tissue forces could be explained. Finally, the present algorithms are the first which are readily available for ballet companies to implement in practice, and may assist in the management of return-to-dance pathways following lower-limb injury. Alongside this paper we provide all data used (Appendix E), complete R code (Appendix E), and an open-source R Shiny application (Chapter 9) housing a graphical user interface for the algorithms.

8.6 Conclusion

Recurrent neural networks were developed using IMU data to estimate internal tissue forces during jumping and landing. This marks the first study detailing the development of a field measure of tissue-specific force in practice. These algorithms outperformed simple linear regression approaches using shank or waist acceleration, which are commonly used in high performance sport. An accompanying app is provided enabling healthcare practitioners to implement these algorithms in field settings. The results agree with similar previous studies suggesting the development of wearable algorithms is a promising area of research for those attempting to measure tissue loads in the field.

CHAPTER 9

OpenTrack: An Open-Source Shiny Application for Calculating and Databasing Training Load Variables Extracted from Wearable Inertial Measurement Unit Data

9.1 Abstract

In elite sport, it is common for science and medicine practitioners to monitor and manipulate an athlete's training load, with the intention of minimizing injury risk and maximizing physical performance. A popular method of quantifying training load is the use of wearable inertial measurement units, from which counts of events such as accelerations, decelerations or jumps, or global movement variables such as PlayerLoad or impact load, can be calculated. The large financial cost of buying or renting these wearable systems means that many organisations outside the world of elite sport may be unable to afford them. This is particularly true in ballet companies and schools, which do not see the same investment as professional sports teams and may face cultural barriers that limit the funding designated for sports science. OpenTrack is an open-source R Shiny application, providing a graphical user interface through which users can upload, process, visualize, and database wearable training load data. OpenTrack is built to interact with either a structured query language (SQL) or a .csv database, allowing users to integrate the platform into existing athlete management software.

9.2 Installation

Opentrack is available via the following url:

https://github.com/joseph-shaw/OpenTrack

9.3 User Interface

The user can interact with OpenTrack across six tabs:

9.3.1 Data Upload

The user may upload data from a central IMU (e.g., at the anterior lower abdomen) and/or data from two IMUs positioned on opposing limbs (e.g., at the left and right thigh). This tab also provides widgets for the user to provide details of the uploaded data (e.g., sampling rate, device orientation).

9.3.2 Data Analysis

Following data upload, the user navigates to this tab to analyse the file. The user can switch between two plots showing a line graph of i) the central IMU data, or ii) the left and right IMU data. These plots are interactive, allowing the user to clip a specific drill, session, or time-period to analyse. At the bottom of this page is a data dashboard which will visualize a summary of the selected time frame. Underneath the main plots is a box allowing the user to enter details of the session which has been clipped (e.g., athlete ID, session type, RPE, comments). If this is the first session entered for an athlete, a secondary tab allows the user to create a new athlete. A screen capture of this tab can be seen in Figure 9.1.

9.3.3 Database

Once a session has been clipped and saved, it is written to the database. The database is stored via either Microsoft SQL Server or a .csv file, depending on the user's settings. From the Database tab, the user can interact with (i.e., view, edit, download) the database. A screen capture of this tab can be seen in Figure 9.2.

9.3.4 Individual Dashboard

The fourth, fifth, and sixth tabs provide dashboards for the user to visualise and analyse the database. The first of these tabs provides detailed plots and tables regarding a single athlete's historical training load. At the top of the page the user simply selects the athlete, the date range, and the time grouping (i.e., into days or weeks), and the dashboard will

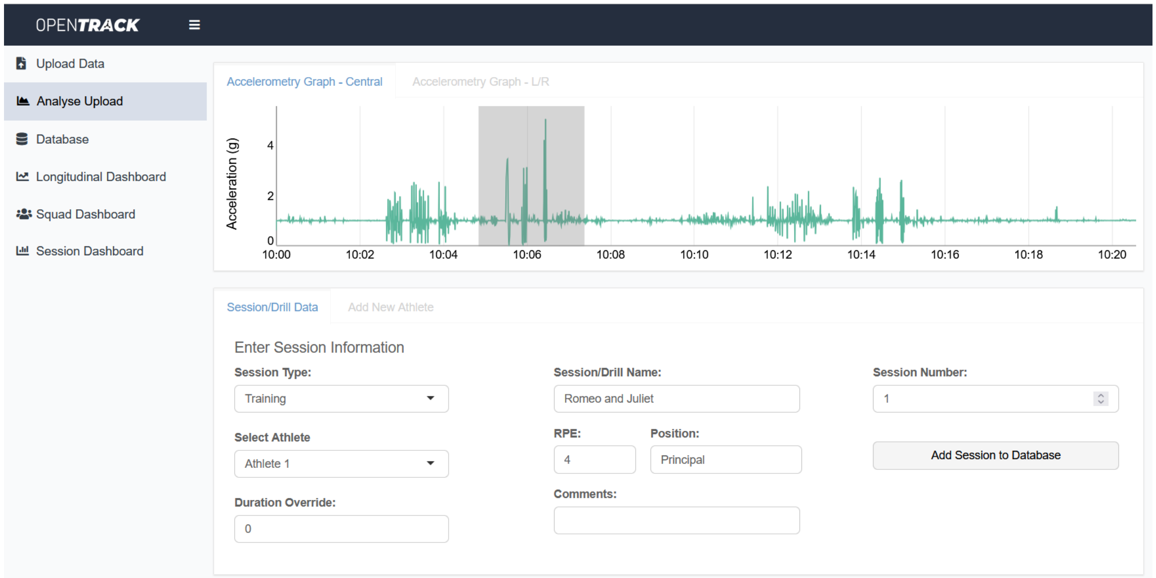


Figure 9.1: Data analysis tab.

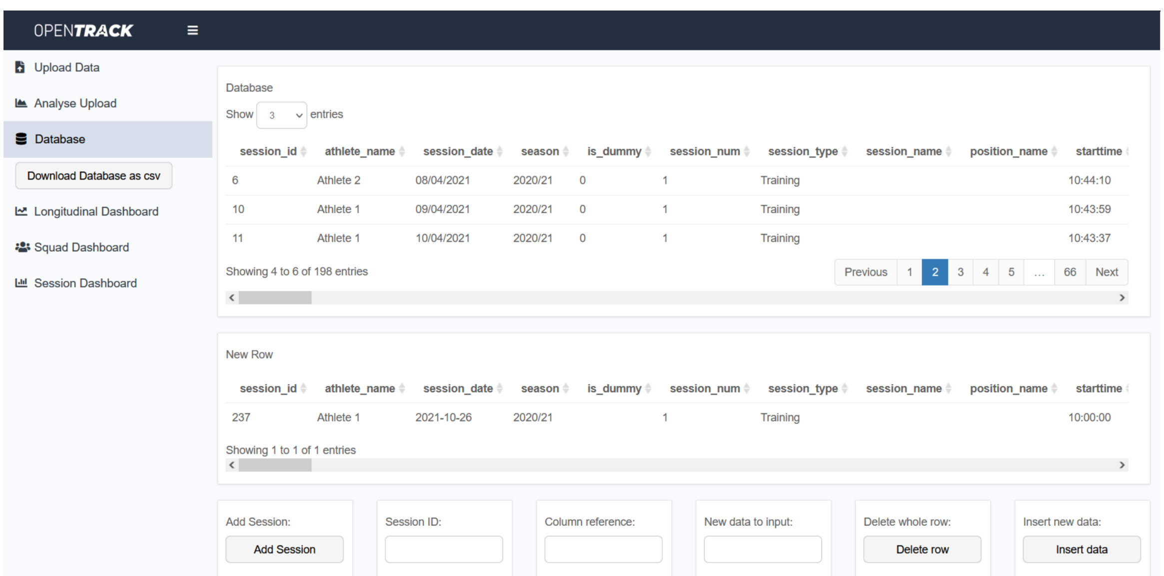


Figure 9.2: Athlete database tab.

populate. The first two plots show the athlete's longitudinal internal and external training load, the latter of which can be interacted with to alter the variable of interest. Underneath these plots, the user can open a dropdown to explore the longitudinal symmetry between left and right IMUs. Finally, another dropdown is available displaying summary data from each individual session saved in the database. A screen capture of this tab can be seen in Figure 9.3.

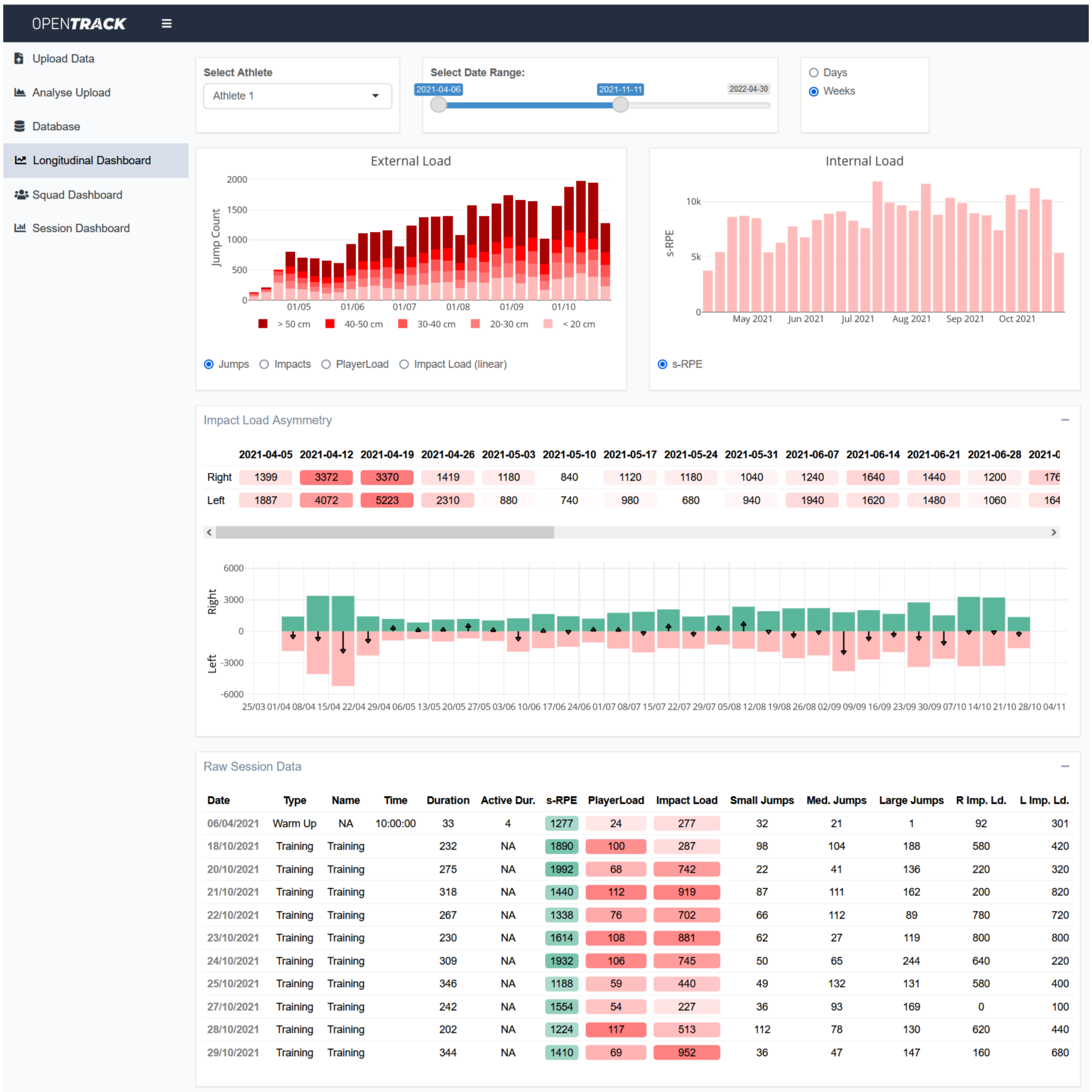


Figure 9.3: Longitudinal dashboard tab.

9.3.5 Squad Dashboard

Here the user can view a snapshot of the historical training loads experienced by multiple athletes. The user simply selects the athletes of interest, date range, and time grouping, and the table will populate. The user can then select a training load variable of their choice to view. A screen capture of this tab can be seen in Figure 9.4.

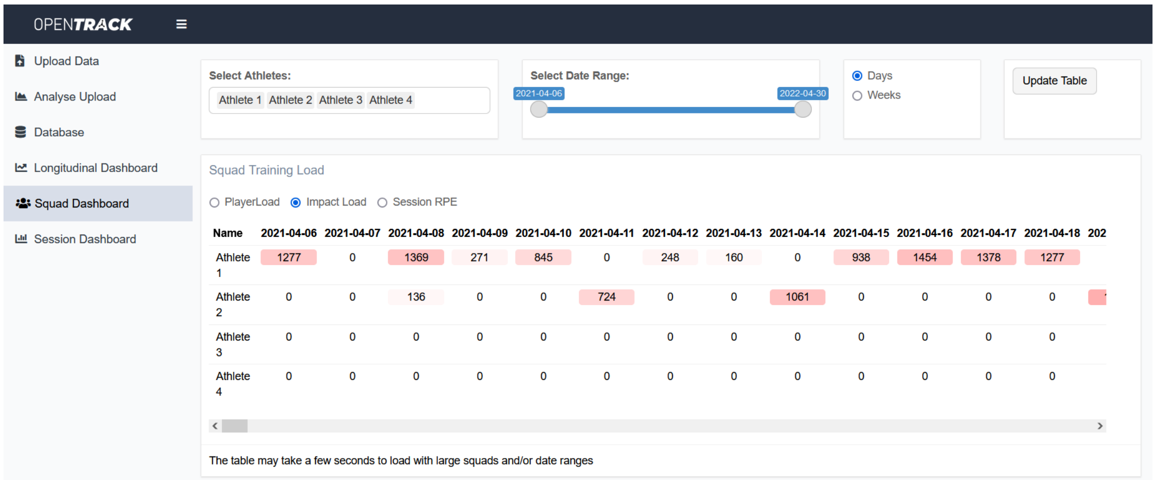


Figure 9.4: Squad dashboard tab.

9.3.6 Session Dashboard

The final tab is designed to visualize a single historical session saved in the database. The user selects the athlete, session date, and session name, and the dashboard will populate. The dashboard is a replica of that shown at the end of the 'Data Analysis' tab. A screen capture of this tab can be seen in Figure 9.5

9.4 Server

The back end of OpenTrack serves three primary functions:

1) Read and analyse wearable data.

2) Database the processed data.

3) Read and process historical sessions.

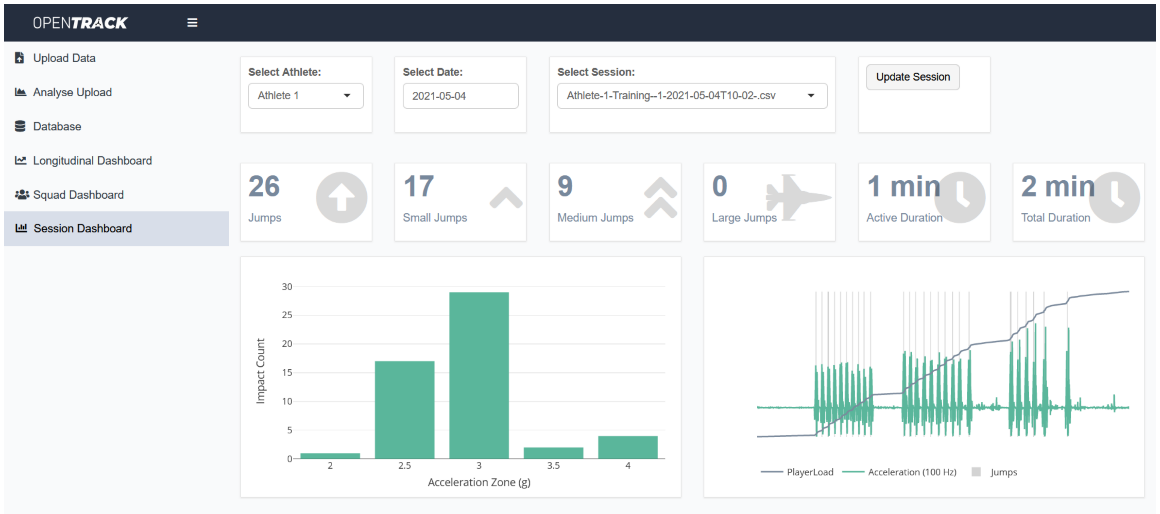


Figure 9.5: Session dashboard tab.

9.5 Training Load Variables

Variables calculated by OpenTrack, and details regarding their calculation, are listed below. Users should note that the evidence for relationships between these variables and outcomes of interest (i.e., performance and injury) is equivocal.

9.5.1 Jump Frequency and Height

To calculate jump frequency and height, OpenTrack uses the algorithm detailed in Chapter 7.

9.5.2 Session Rating of Perceived Exertion

When entering session details in the 'Analyse Session' tab, an RPE entry box is provided. This value is multiplied by the duration of the session (or the 'duration override' value, if entered) to calculate the s-RPE. For use of s-RPE with professional ballet dancers, readers are directed towards Chapter 6.

9.5.3 PlayerLoad

OpenTrack calculates PlayerLoad™ in line with that described by Catapult [262]. PlayerLoad™ is calculated following data filtering. Readers are directed elsewhere for further discussion on PlayerLoad™ [263, 57].

$$\sum \sqrt{\frac{(\mathrm{fwd}_{t=i+1} - \mathrm{fwd}_{t=i}) + (\mathrm{side}_{t=i+1} - \ \mathrm{side}_{t=i}) + (\mathrm{up}_{t=i+1} - \ \mathrm{up}_{t=i})}{100}}$$

9.5.4 Impact load

OpenTrack calculates impact load in line with the description from IMeasureU [264]: "the sum of the intensities created from every impact measured" during a session. For example, if a player recorded five impacts, the peak intensities of which were 1, 2, 3, 4, and 5 g, the impact load would be calculated as (1 + 2 + 3 + 4 + 5 = 15 AU).

9.5.5 Ground Reaction Force

To estimate ground reaction force, OpenTrack uses the algorithm detailed in Chapter 8.

9.5.6 Achilles Tendon, Patellar Tendon, and Tibial Bone Force

To estimate Achilles tendon, patellar tendon, and tibial bone force, OpenTrack uses the algorithm detailed in Chapter 8.

CHAPTER 10

General Discussion

10.1 Context

Research in sports medicine has demonstrated the importance of understanding and managing athletic training load. Despite the high dance exposure durations reportedly undertaken by professional ballet dancers, relatively little research has been conducted, and load management is not yet the norm in ballet companies. This thesis, therefore, had three primary aims: i) to understand the training load demands experienced by professional ballet dancers; ii) to explore the relationship between balletic training load and musculoskeletal injury; and iii) to provide professional ballet companies with practical methods and recommendations for the management of training load. This discussion will address each aim in turn, followed by their practical applications, and potential avenues for further research.

10.2 Training Loads in Professional Ballet

The systematic review presented in Chapter 3 explored existing research into the activity demands and physiological responses observed in professional ballet. At the level of a single class, rehearsal, or performance, ballet is intermittent, featuring sequences of high intensity movements interspersed with periods of rest. The demands of ballet vary between session types: the metabolic intensity of ballet class is limited due to the long rest breaks between exercises [4, 136], however, in featured performance roles, dancers frequently reach close to maximal intensities [125]. In the case of corps de ballet dancers, on the other hand, much of a performance may be spent at rest [46]. The jumping demands of ballet have only been investigated in performances [46, 137], during which dancers jump at a rate of ~5 jumps·min^{-1}, exceeding the rates of jumping in sports such as volleyball [152] and basketball [153]. Given the high frequency of jumping and the high rate of injuries resulting from jumping and landing movements in professional ballet dancers [163], the management of jump load was identified as a primary focus for research.

Seven studies were identified as having reported some measure of more general training load demands (i.e., beyond the demands of a single session); Four of these, however, only provide superficial data regarding ‘normal’ dance exposure durations. Though these studies are limited in their methodological approaches, they are consistent in their results, typically reporting values greater than 30 h of dance per week. These values are much higher than comparable training and performance exposure durations reported in sporting research [152, 155, 156], however, without greater detail around the make-up or variation of these values, they provide little practical value. Similarly, one study reported a company’s seasonal show count—ranging from 142-145—however, the proportion of shows performed by each company dancer was not stated. Studies using wearable technology [141, 142] revealed that whilst total activity levels are high (> 7.5 h·day^{-1}), much of this time is spent at relatively low intensities. Unlike recent training load research in sport, these studies report metabolic equivalents, but not variables related to musculoskeletal load (e.g., jumps, accelerations, decelerations, etc.).

A primary finding of Chapter 3 was the scarcity of longitudinal research into the demands of a ballet schedule. This finding echoes qualitative research in which dancers identified a lack of understanding around the structure of the training season, and the imbalance in load across the season, as major factors contributing to injury [12]. Chapter 5, therefore, sought to provide a more comprehensive analysis of longitudinal rehearsal and performance volume in a professional ballet company. Rank-dependent, dancers completed between 20 and 30 h of dance per week on average, though large variation in these figures was evident from week-to-week, and across the season. In fact, weeks in which dancers exceeded 40 h of dance per week were frequent, particularly in the ranks of soloist, first artist, and artist. Rapid increases in dance volume were also common, with week-to-week increases in dance hours of $> 50\%$ taking place in a quarter of weeks. Much of this variation likely reflects the overlapping nature of the repertoire; throughout the season at least three productions are typically in rehearsal or performance concurrently, whilst at the busiest times there were five separate productions underway. Training loads in professional ballet, therefore, appear to be irregular and volatile; it is important to understand the load-injury relationship in ballet such that artistic and healthcare teams can address load-related health problems through appropriate periodisation.

10.3 The Load-Injury Relationship in Professional Ballet

The load-injury relationship in dance has previously been investigated on three occasions, though methodological limitations undermine or restrict the conclusions which can be drawn. Chapter 4 presented a five-season cohort study exploring the relationships between individual risk factors, accumulated dance volume, and injury in professional ballet. Shared frailty models were fitted to 1332 medical attention injuries (427 of which were time-loss injuries), with age, sex, company rank, injury history, and the accumulated dance volume variables: 7-day accumulated dance hours, 28-day accumulated dance hours, and week-to-week change in dance hours, included as independent variables. In line with similar research in sport, rapid increases in volume were associated with both medical attention and time-loss overuse injuries. Unusually, however, hazard ratios for overuse medical attention injuries were lower in following 7-day periods of greater accumulated dance hours; a result in opposition to previous findings [73]. Several individual risk factors also demonstrated relationships with injury rates. Consistent with many research studies in sport, prior injury rate was positively associated with the hazard ratio for overuse injury. No relationship was observed between sex and injury rates; however, a relationship was observed between company rank and injury rates, with greater hazard ratios in soloists compared with the corps de ballet. Only age was associated with traumatic injury rates, with older dancers incurring a higher rate of traumatic injury.

From a methodological standpoint, Chapter 4 builds on previous load-injury research in dance. Most notably previous studies have been limited by an underpowered sample of injury events, exclusion of medical attention injuries, a lack of exposure measure, and overly simplistic modelling approaches. The present investigation addresses these problems, though is nonetheless imperfect. For example, whilst the shared frailty model accounted for recurrent events and time-varying covariates, it may be inferior to a multi-state approach, whereby non-time-loss injuries operate as a middle ground between uninjured and time-loss injury states. Moreover, whilst the number of injuries observed exceeds those observed in previous research in dance, this number was insufficient to target specific tissue types and anatomical locations of injury. Finally, Chapter 4 is only one of many studies investigating the load-injury relationship across athletic populations; whilst it provides novel insight into healthcare in dance, it should not be interpreted in isolation, but in the context of a wider body of research. As such, the resulting recommendations for load management in professional ballet (discussed in section 10.5) are based on both the present research and prior research in sport.

Whilst aspects of the load-injury relationship in professional ballet remain unclear, researchers should be cautious when planning training load research in this population. Given the multidimensional nature of athletic injury, and the multitude of methodological and statistical pitfalls encountered in load-injury research, these studies should be undertaken only when such factors can be overcome. To achieve sufficient statistical power to investigate injury at either a tissue level, anatomical location level, or at the level of a specific diagnosis, it is likely that multi-centre studies will be required. Researchers should consider that where such sample sizes are not feasible, research quality is likely to be higher by targeting alternative response-to-load variables, for example, physical performance or perceived wellbeing.

10.4 Methods for Measuring Training Load in Ballet

Prior to this thesis, ballet healthcare practitioners seeking to measure the training loads experienced by ballet dancers had a limited selection of methodological approaches from which to choose. This limited selection results from a lack of research into the methodological validity of potential measures, or a lack of accessibility to those measures which have been validated, for example, due to the need for data science expertise, because data and algorithms have not been shared openly, or because of the need for high-end equipment. This thesis provides science and medicine practitioners with three viable methods for quantifying load which do not require high-end equipment; this section will explore each of those, in reference to what was previously available, and areas for further research and development.

10.4.1 Session-Rating of Perceived Exertion

The study contained in Chapter 6 of this thesis is the first to investigate the validity of s-RPE in professional ballet dancers, within which very large positive relationships were observed between s-RPE and TRIMP scores across all sessions. These relationships were stronger than those demonstrated in non-professional ballet or contemporary dancers, and suggest that s-RPE provides a valid measure of the metabolic intensity of a session without the need for equipment. This overcomes two practical issues faced by ballet companies: i) training load can be measured for performances, in which alternative measures of internal training load (e.g., HR straps) may not be an option; and ii) large numbers of dancers can be monitored without needing to purchase large quantities of equipment, or process large volumes of data.

Healthcare practitioners should note that whilst s-RPE may facilitate valid measurement of metabolic training load, at present, its use as a measure of other loading constructs is inadvisable. This is important to state given that many of the health issues faced by dancers are overuse musculoskeletal complaints, and often associated with specific movements. Whilst metabolic training load may correlate with mechanical load, healthcare practitioners should be cautious of manipulating the former in expectation of a corresponding change in the latter. Put simply, optimal periodisation of metabolic training load variables will not necessarily mitigate the risk of common musculoskeletal ballet injuries. Given this stipulation, research into the use of differential RPEs in ballet is a potential avenue through which the most common load-related injuries may be better understood. For example, the question 'what was the intensity of your rehearsal?" may be redirected towards a specific body part ('what was the lower-limb muscular intensity of your rehearsal") or movement ('what was the intensity of *pointe* work in your rehearsal?"). This may be a particularly beneficial strategy for quantifying the loads associated with the primary mechanisms of injury in ballet: *pointe* load, where no alternative strategy currently exists; or jump load, for which barriers to the use of wearable IMUs may exist, for example, a lack of equipment, or a lack of staff with appropriate expertise. Similarly, even where staff and equipment are available, differential RPEs may be more scalable to a large company of dancers compared with wearable systems.

10.4.2 Jump Load

The importance of quantifying jump load has previously been outlined in the literature [154]. In ballet, jumping and landing actions are implicated in 27% (women) and 38% (men) of all time-loss injuries [163]. As such, ensuring jump load is appropriately prescribed—or at least not inadvertently mismanaged—is paramount. The algorithm presented in Chapter 7 demonstrates a high level of validity in both the detection of jumping events (sensitivity = 0.95, precision = 0.95, miss rate = 0.05) and the measurement of jump height (r_{rm} = 0.97, bias = +1.2 cm, 95% LoA: -4.9 to 7.2 cm, MAE: 2.6 cm).

The relationship between jump load and injury risk is likely weaker than that between tissue-specific forces and injury risk. The value in jump load, however, is in its simplicity and relevance to the ballet world. Conversations around training load with a choreographer or ballet coach are likely to be more productive, and result in the desired change, when the load variable in question is context specific. In this respect, jump load is a metric which can be understood, manipulated, and even directly observed by a non-specialist. An accelerometer worn at the waist is relatively discreet in comparison to other common wearables which may require larger devices, inconvenient clothing (e.g., vests), or multiple sensors. As such, the approach outlined in Chapter 6 is likely to result in greater dancer compliance with regular monitoring, enable data collection on stage, and facilitate discussions with artistic staff.

The quantification of jump load in professional ballet may be further developed through more detailed classification of jump types. For example, identification of the take-off or landing limb(s) during a jump may be useful during late-stage rehabilitation pathways from unilateral injuries. Similarly, identification of ballet-specific jumps may be useful in identifying the mechanism of an injury, or managing a return-to-dance pathway following a traumatic injury associated with a specific movement. To this end, previous research has demonstrated more specific movement detection during ballet using complex algorithms and a greater number of sensors [114]. Importantly, however, end-user implementation must be considered; unless these algorithms are embedded into easy-to-use applications, and require only discreet sensors, they are unlikely to be adopted into practice.

10.4.3 Tissue-specific Force

Chapter 8 detailed the development and evaluation of deep learning algorithms for the estimation of lower limb physiological tissue forces during jumping and landing movements. This approach has been demonstrated conceptually (i.e., using lab-based signals that could theoretically be derived from wearables) across different running speeds, though this is the first study to implement this method in practice, and the first time this approach has been used for jumping and landing movements. For tibial, patellar tendon, Achilles tendon, and ground reaction force, the algorithms considerably outperformed single variable linear regression using waist or shank resultant acceleration, particularly for the estimation of peak forces. This finding is consistent with previous suggestions that there is little biomechanical rationale supporting the notion that tibial acceleration is indicative of lower limb tissue forces [117]. Whilst the present research did not investigate the relationship between shank acceleration and lower-limb tissue forces during more general athletic movements (e.g., running, cutting, shuffling, etc.), some speculation is justified. By extrapolating the present results, and considering the lack of biomechanical rationale, it seems counterintuitive to continue using shank accelerations as a measure of lower limb load in athletic activities.

The greater performance of the machine learning approach, compared with common methods used in the field (i.e., shank and waist acceleration) suggests there are considerable improvements to be made in the measurement of tissue-specific biomechanical load. Methodological improvements over the current approach (inclusion of orientation, greater sample size, more diverse movements, etc.) provide immediate avenues for improvements in algorithm performance, whilst a host of other factors may facilitate further refinement. These may include additional or alternative sensor types (e.g., pressure sensing insoles), different sensor locations, different model types, ensemble learning, and alternative model architecture, to name a few. Academics and healthcare practitioners, however, should be cautious in pursuing this research area in the hope of achieving accurate injury prediction. Given the high degree of accuracy needed to reach this goal, combined with the stochastic nature of tissue failure, and the multifactorial and changeable nature of tissue capacity, it seems likely that individualised models, and vast improvements in algorithm performance would be needed before this becomes a reality. Such goals are unlikely to be reached in the short term and should not be the focus of applied sports science support.

10.5 Recommendations for the Management of Training Load in Ballet

Chapter 4 demonstrated that in a professional ballet company, linear increases in both medical attention and time-loss injury rates are observed with increasing week-to-week changes in dance exposure time. This finding aligns with a large body of research in sport, suggesting that rapid increases in training load are associated with injury. Furthermore, Chapter 5 illustrated that without company-wide load management strategies, dancers are frequently subject to common risk factors for injury, namely extremely high and rapidly changing rehearsal and performance volume. Appropriate management of balletic training load is, therefore, advisable to mitigate the risk of injury in professional ballet companies.

Current guidelines for the management of training load in ballet should be consistent with those applying to the field of sports medicine:

- Avoid rapid changes in training load.
- Avoid periods of very-high training load.
- Maintain moderate-to-high training loads over the long term.

More specific recommendations, at this point, are not justified based on current research. Importantly, unique barriers to meeting these recommendations exist in dance. Artistic and healthcare practitioners working in ballet should apply their contextual understanding of the environment when considering these guidelines. For example, rapid changes in load may be unavoidable following a last-minute cast change; situations such as this should be adapted to through manipulation of other rehearsals and performances, and through the provision of appropriate management and recovery strategies. Less obvious spikes in training load may be observed at the onset of a new ballet because of the differences in choreography. If dancers are required to rehearse and perform classical repertoire immediately following the completion of a contemporary ballet, for example, dancers may experience a sudden increase in jump or *pointe* load, despite no changes in the metabolic demands or the volume of rehearsals. Therefore, it is imperative that load management is proactive where possible (i.e., takes place at the repertoire planning and casting stages), and is not merely reactive to an unforeseen event.

10.5.1 Intensive Longitudinal Training Load Monitoring

The use of intensive longitudinal training load monitoring—i.e., daily collection of athlete-specific training loads—is the norm in many elite level sports. It is, therefore, likely to be seen as the goal for many healthcare departments in professional ballet companies. Whilst this goal is understandable, a plethora of challenges and obstacles stand between the current reality and that target.

For many ballet companies, the logistical challenges of collecting and managing daily training load data—and particularly wearable data—will be insurmountable in the short term. Where this level of data is collected in professional sports teams, there is often a sports scientist or data scientist employed whose sole job is to record and manage the training load data of a single squad of 20–30 athletes. In contrast, not only are ballet companies often comprised of larger 'squads' (in some cases ~100 dancers), but few employ full-time sports scientists. For those which do, these individuals are typically responsible for the delivery of a holistic sports science approach (e.g., strength and conditioning, biomechanics, physical testing, nutrition, etc.), and not solely training load management. Furthermore, acquiring a wearable monitoring device for an entire company of dancers would come at a considerable expense. Therefore, it would require a drastic increase in funding for ballet healthcare teams to be able to afford the technology and personnel to overcome the practical barriers to daily load monitoring.

Given the logistical challenges of daily load monitoring, and the current level of sports science support provided by professional ballet companies, investing in intensive longitudinal load monitoring is simply not an effective use of time nor resources. This is not to say that load management in ballet is not important; but instead that such detailed quantification of load is unnecessary when alternative approaches are likely to be easier to implement and provide a greater benefit. Chapter 5 demonstrated both the extreme volumes of dance involved in day-to-day ballet rehearsal and performance schedules, as well as the inconsistency in these working volumes from week-to-week; Chapter 4 identified an association between larger week-to-week changes in exposure and the risk of musculoskeletal injury. To this end, it is unlikely that an individualised monitoring approach is needed to address these problems; instead, simple company-wide approaches to load management should be employed until these gross inefficiencies are improved upon. For example, educating artistic staff on training principles such as progressive overload, periodisation, and recovery; including medical voices in discussions around repertoire planning; and adjusting whole-company loads based on scheduled dance volume. Furthermore, small modifications to a dancer's training based on wearable data should be secondary to ensuring dancers are following good nutritional practices, recovering effectively between rehearsals and shows, being given the opportunity to get optimal sleep each night, and engaging in consistent and well-directed strength and conditioning sessions. This sentiment is expressed in Figure 10.1, which presents a proposed hierarchy for the implementation of sports science services within ballet companies. This thesis outlines a strategy in which company-wide intensive longitudinal load monitoring is only implemented once more fundamental building blocks are in place. At present, few professional ballet companies, if any, have these foundations in place.

10.5.2 Where Does Intensive Load Management Fit Within Sports Science and Medicine Provision in Ballet?

Given the preceding critical evaluation of intensive longitudinal load monitoring in professional ballet, it is important to identify several areas in which intensive longitudinal load monitoring may be beneficial. Firstly, regular monitoring may provide value in cases where a dancer's case becomes medicalised, i.e., during injury rehabilitation or following the initial presentation of musculoskeletal injury symptoms. In these situations, i) the risk of mismanaging dancer training load is greater, and is accompanied by more severe consequences; and ii) healthcare practitioners have greater scope to influence the activity undertaken by the dancer in upcoming sessions, and thus the data is more likely to be actioned. Secondly, daily load monitoring may contribute to applied research questions, and thus the benefits extend beyond simply the impact that monitoring has on a single dancer's health and performance. For example, understanding the jump load associated with a specific performance or role may facilitate improvements in the physical preparation of multiple dancers across multiple seasons, or may contribute to the decision-making process surrounding repertoire selection.

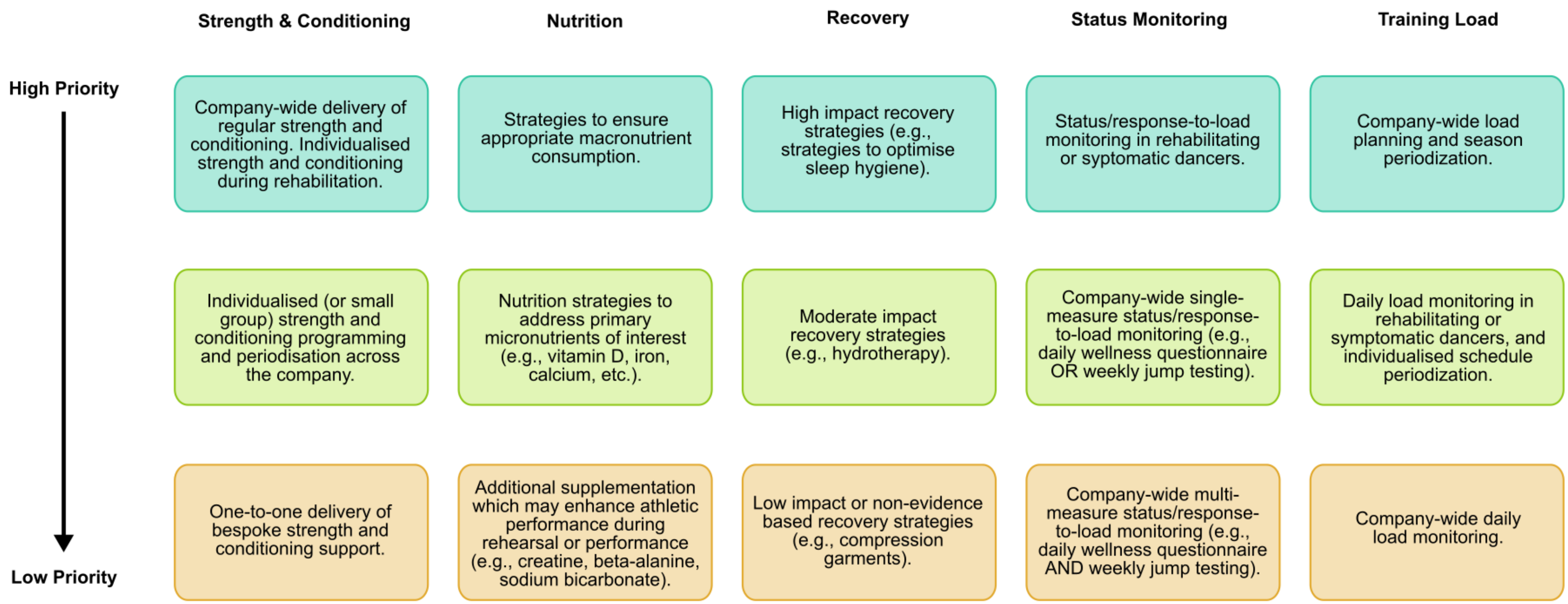


Figure 10.1: A proposed model for implementing sports science support in professional ballet companies. The priority of various degrees of training load monitoring is presented relative to strength and conditioning, nutrition [265], recovery [266, 267], and status monitoring [268] strategies.

10.5.3 Conclusion

This thesis investigated training load in professional ballet and the validity of methods for its quantification. A more comprehensive understanding of the training demands undertaken by professional ballet dancers was attained through two literature reviews and an analysis of five seasons of rehearsal and performance scheduling data at an elite professional ballet company. Dancers were found to undertake large volumes of dance, however, dance hours fluctuated widely from week-to-week. Individual risk factors and patterns of dance volume associated with injury rates were identified, and used to inform best practice recommendations for the management of training load. Three methods for quantifying training load were found to be valid. For the quantification of internal training load, s-RPE demonstrated very large linear relationships with HR-derived measures of internal training load. For the measurement of external training load, two novel IMU algorithms were developed. Firstly, a rule-based classifier for measuring jump frequency and height demonstrated a high degree of accuracy, providing a simple means of managing jump load. Secondly, a series of recurrent neural networks were developed to facilitate the measurement of tissue-specific forces outside of a laboratory, outperforming single variable linear regression approaches for the measurement of Achilles tendon, patellar tendon, and tibial force. Open-source software was developed and presented to house these algorithms, and database and visualize longitudinal training load data. The volume of training load in professional ballet is high, however, with specific efforts to periodise a company's rehearsal and performance schedule, key risk factors can be minimised. Valid methods for monitoring dancer load have been presented, which may facilitate research and rehabilitation.

BIBLIOGRAPHY

[1] C Lee. *Ballet in Western Culture: A History of Its Origins and Evolution*. Routledge, 2002.

[2] Rachel Evelyn Ward. *Biomechanical perspectives on classical ballet technique and implications for teaching practice*. Dissertation, University of New South Wales, 2012.

[3] The Royal Ballet School.

[4] Peter G. Schantz and Per-Olof Åstrand. Physiological characteristics of classical ballet. *Medicine and Science in Sports and Exercise*, 16(5):472–476, 1984.

[5] Jerald L. Cohen, Prem K. Gupta, Edgar Lichstein, and Kul D. Chadda. The Heart of a Dancer: Noninvasive Cardiac Evaluation of Professional Ballet Dancers. *The American Journal of Cardiology*, 45(5):959–965, 1980.

[6] Emily Twitchett, Yiannis Koutedakis, and Matthew A. Wyon. Physiological Fitness and Professional Classical Ballet Performance: a Brief Review. *Journal of Strength and Conditioning Research*, 23(9):2732–2740, 2009.

[7] Yiannis Koutedakis and Athanasios Jamurtas. The Dancer as a Performing Athlete: Physiological Considerations. *Sports Medicine*, 34(10):651–661, 2004.

[8] Nick Allen and Matthew A. Wyon. Dance medicine: Artist or athlete? *Sportex Medicine*, 35(May):6–9, 2008.

[9] Michael K. Drew and Caroline F. Finch. The Relationship Between Training Load and Injury, Illness and Soreness: A Systematic and Literature Review. *Sports Medicine*, 46(6):861–883, 2016.

[10] Arne Jaspers, Michel S. Brink, Steven G.M. Probst, Wouter G.P. Frencken, and Werner F. Helsen. Relationships Between Training Load Indicators and Training Outcomes in Professional Soccer. *Sports Medicine*, 47(3):533–544, 2017.

[11] Jordan L. Fox, Robert Stanton, Charli Sargent, Sally Anne Wintour, and Aaron T. Scanlan. The Association Between Training Load and Performance in Team Sports: A Systematic Review. *Sports Medicine*, 48(12):2743–2774, 2018.

[12] Caroline Bolling, Rogier M. van Rijn, H.Roeline Pasman, Willem van Mechelen, Janine H. Stubbe, Roeline Pasman, Willem van Mechelen, and Janine H. Stubbe. In your shoes: a qualitative study on the perspectives of professional dancers and staff regarding dance injury and its prevention. *Translational Sports Medicine*, 4(3):386–394, 2021.

[13] Young-Eun Noh, Tony Morris, and Mark B. Andersen. Occupational Stress and Coping Strategies of Professional Ballet Dancers in Korea. *Medical Problems of Performing Artists*, 24(3):124–134, 2009.

[14] Nick Allen, Alan M. Nevill, John H.M. Brooks, Yiannis Koutedakis, and Matthew A. Wyon. The effect of a comprehensive injury audit program on injury incidence in ballet: a 3-year prospective study. *Clinical Journal of Sport Medicine*, 23(5):373–378, sep 2013.

[15] Nick Allen, Alan Nevill, John Brooks, Yiannis Koutedakis, and Matthew A. Wyon. Ballet Injuries: Injury Incidence and Severity Over 1 year. *Journal of Orthopaedic & Sports Physical Therapy*, 42(9):781–790, 2012.

[16] Tim J Gabbett. The training-injury prevention paradox: should athletes be training smarter and harder? *British Journal of Sports Medicine*, 50(5):273–280, 2016.

[17] Torbjørn Soligard, Martin Schwellnus, Juan Manuel Alonso, Roald Bahr, Ben Clarsen, H. Paul Dijkstra, Tim Gabbett, Michael Gleeson, Martin Hägglund, Mark R. Hutchinson, Christa Janse Van Rensburg, Karim M. Khan, Romain Meeusen, John W. Orchard, Babette M. Pluim, Martin Raftery, Richard Budgett, and Lars Engebretsen. How much is too much? (Part 1) International Olympic Committee consensus statement on load in sport and risk of injury. *British Journal of Sports Medicine*, 50(17):1030–1041, 2016.

[18] Franco M. Impellizzeri, Samuele M. Marcora, and Aaron J. Coutts. Internal and External Training Load: 15 Years On. *International Journal of Sports Physiology and Performance*, 14(2):270–273, 2019.

[19] Stephen W. West, Jo Clubb, Lorena Torres-Ronda, Daniel Howells, Edward Leng, Jason D. Vescovi, Sean Carmody, Michael Posthumus, Torstein Dalen-Lorentsen, and Johann Windt. More than a Metric: How Training Load is Used in Elite Sport for Athlete Management. *International Journal of Sports Medicine*, 42(4):300–306, 2021.

[20] Judd T. Kalkhoven, Mark L. Watsford, Aaron J. Coutts, W. Brent Edwards, and Franco M. Impellizzeri. Training Load and Injury: Causal Pathways and Future Directions. *Sports Medicine*, 51(6):1137–1150, 2021.

[21] Aaron Coutts, Tom Kempton, and Stephen Crowcroft. Developing athlete monitoring systems: Theoretical basis and practical applications. In M. Kellmann and J Beckmann, editors, *Sport, Recovery and Performance: Interdisciplinary Insights*, number October, pages 19–32. Abingdon, 2018.

[22] Atko Viru and Mehis Viru. Nature of training effects. *Exerc Sport Sci*, 6(7):67–95, 2000.

[23] Rod W. Fry, Alan R. Morton, and David Keast. Overtraining in Athletes: An Update. *Sports Medicine*, 12(1):32–65, 1991.

[24] Thomas W. Calvert, Eric W. Banister, Margaret V. Savage, and Tim Bach. A Systems Model of the Effects of Training on Physical Performance. *IEEE Transactions on Systems Man and Cybernetics*, 6:94–102, 1976.

[25] Korey Kasper. Sports Training Principles. *Current Sports Medicine Reports*, 18(4):95–96, 2019.

[26] Kathryn Burnet, Simon Higgins, Elizabeth Kelsch, Justin B. Moore, and Lee Stoner. The effects of manipulation of Frequency, Intensity, Time, and Type (FITT) on exercise adherence: A meta-analysis. *Translational Sports Medicine*, 3(3):222–234, 2020.

[27] William G. Hopkins. Quantification of Training in Competitive Sports: Methods and Applications. *Sports Medicine*, 12(3):161–183, 1991.

[28] Mark Burnley and Andrew M. Jones. Oxygen uptake kinetics as a determinant of sports performance. *European Journal of Sport Science*, 7(2):63–79, 2007.

[29] Mark Burnley and Andrew M. Jones. Power–duration relationship: Physiology, fatigue, and the limits of human performance. *European Journal of Sport Science*, 18(1):1–12, 2018.

[30] R. Hugh Morton, John R. Fitz-Clarke, and Eric W. Banister. Modeling human performance in running. *Journal of Applied Physiology*, 69(3):1171–1177, 1990.

[31] Sally Edwards. High performance training and racing. In *The Heart Rate Monitor Book*, pages 113–123. Feet Fleet Press, Sacramento, CA, 8 edition, 1993.

[32] Alejandro Lucía, Jesús Hoyos, Alfredo Santalla, Conrad Earnest, and José L. Chicharro. Tour de France versus Vuelta a España: Which is harder? *Medicine and Science in Sports and Exercise*, 35(5):872–878, 2003.

[33] Vincenzo Manzi, Ferdinando Iellamo, Franco Impellizzeri, Stefano D'Ottavio, and Carlo Castagna. Relation between individualized training impulses and performance in distance runners. *Medicine and Science in Sports and Exercise*, 41(11):2090–2096, 2009.

[34] Carl Foster, Jessica A. Florhaug, Jodi Franklin, Lori Gottschall, Lauri A. Hrovatin, Suzanne Parker, Pamela Doleshal, and Christopher Dodge. A New Approach to Monitoring Exercise Training. *Journal of Strength and Conditioning Research*, 15(1):109–115, 2001.

[35] Gunnar Borg. Borg's Perceived Exertion And Pain Scales. *Human Kinetics*, jul 1998.

[36] Franco M. Impellizzeri, Ermanno Rampinini, Aaron J. Coutts, and Samuele M. Marcora. Use of RPE-based training load in soccer. *Medicine & Science in Sports & Exercise*, 36(6):1042–1047, 2004.

[37] Helen Alexiou and Aaron J. Coutts. A comparison of methods used for quantifying internal training load in women soccer players. *International Journal of Sports Physiology and Performance*, 3(3):320–330, 2008.

[38] Luiz A. Perandini, Thiago A. Siqueira-Pereira, Nilo M. Okuno, Lúcio F. Soares-Caldeira, and Fabio Y. Nakamura. Use of session RPE to training load quantification and training intensity distribution in taekwondo athletes. *Science and Sports*, 27(4):25–30, 2012.

[39] Monoem Haddad, Georgios Stylianides, Leo Djaoui, and Alexandre Dellal. Session-RPE Method for Training Load Monitoring: Validity, Ecological Usefulness and Influencing Factors. *Frontiers in Neuroscience*, 11(612):1:14, 2017.

[40] Maurizio Fanchini, Ivan Ferraresi, Roberto Modena, Federico Schena, Aaron J. Coutts, and Franco M. Impellizzeri. Use of CR100 Scale for Session-RPE in Soccer and Interchangeability With CR10 Authors:. *International Journal*, 14(2):156–162, 2018.

[41] Shaun J. McLaren, Andrew Smith, Iain R. Spears, and Matthew Weston. A detailed quantification of differential ratings of perceived exertion during team-sport training. *Journal of Science and Medicine in Sport*, 20(3):290–295, 2017.

[42] Stephen Lyman, Glenn S. Fleisig, John W. Waterbor, Ellen M. Funkhouser, Leavonne Pulley, James R. Andrews, E. David Osinski, and Jeffrey M. Roseman. Longitudinal study of elbow and shoulder pain in youth baseball pitchers. *Medicine & Science in Sports & Exercise*, 33(11):1803–1810, 1998.

[43] John W. Orchard, Peter Blanch, Justin Paoloni, Alex Kountouris, Kevin Sims, Jessica J. Orchard, and Peter Brukner. Fast bowling match workloads over 5 – 26 days and risk of injury in the following month. *Journal of Science and Medicine in Sport*, 18:26–30, 2015.

[44] Daniele Conte, Terence G. Favero, Corrado Lupo, Fabio M. Francioni, Laura Capranica, and Antonio Tessitore. Time-Motion Analysis of Italian Elite Women's Basketball Games: Individual and Team Analyses. *Journal of Strength and Conditioning Research*, 29(1):144–150, 2015.

[45] M.U. Deutsch, G.A. Kearney, and N.J. Rehrer. Time-motion analysis of professional rugby union players during match-play. *Journal of Sports Sciences*, 25(4):461–472, 2007.

[46] Matthew A. Wyon, Emily Twitchett, Yiannis Koutedakis, and Manuela Angioi. The day-to-day workload of ballet dancers. *International Symposium on Performance Science*, pages 143–148, 2011.

[47] Norhafizan Ahmad, Raja Ariffin Raja Ghazilla, Nazirah M. Khairi, and Vijayabaskar Kasi. Reviews on Various Inertial Measurement Unit (IMU) Sensor Applications. *International Journal of Signal Processing Systems*, 1(2):256–262, 2013.

[48] Manon Kok, Jeroen D. Hol, and Thomas B. Schön. Using inertial sensors for position and orientation estimation. *Foundations and Trends in Signal Processing*, 11(1-2):1–153, 2017.

[49] Richard P. Troiano, James J. McClain, Robert J. Brychta, and Kong Y. Chen. Evolution of accelerometer methods for physical activity research. *British Journal of Sports Medicine*, 48(13):1019–1023, 2014.

[50] Michael Higgins, P. David Halstead, Lynn Snyder-Mackler, and David Barlow. Measurement of impact acceleration: Mouthpiece accelerometer versus helmet accelerometer. *Journal of Athletic Training*, 42(1):5–10, 2007.

[51] Krzysztof Buśko, Zbigniew Staniak, Mirosława Szark-Eckardt, Pantelis Theodoros Nikolaidis, Joanna Mazur-Rózycka, Patrycja Łach, Radosław Michalski, Jan Gajewski, and Michał Górski. Measuring the force of punches and kicks among combat sport athletes using a modified punching bag with an embedded accelerometer. *Acta of Bioengineering and Biomechanics*, 18(1):47–54, 2016.

[52] Ina Janssen and Alexi Sachlikidis. Validity and reliability of intra-stroke kayak velocity and acceleration using a GPS-based accelerometer. *Sports Biomechanics*, 9(1):47–56, 2010.

[53] Tim Steels, Ben Van Herbruggen, Jaron Fontaine, Toon De Pessemier, David Plets, and Eli De Poorter. Badminton activity recognition using accelerometer data. *Sensors*, 20(17):1–16, 2020.

[54] David Whiteside, Olivia Cant, Molly Connolly, and Machar Reid. Monitoring Hitting Load in Tennis Using Inertial Sensors and Machine Learning Authors:. *International journal of Sports Physiology and Performance*, 12(9):1212–1217, 2017.

[55] Dustin A. Bruening, Riley E. Reynolds, Chris W. Adair, Peter Zapalo, and Sarah T. Ridge. A sport-specific wearable jump monitor for figure skating. *PLoS ONE*, 13(11):1–13, 2018.

[56] Sarah Whitehead, Kevin Till, Dan Weaving, and Ben Jones. The Use of Microtechnology to Quantify the Peak Match Demands of the Football Codes: A Systematic Review. *Sports Medicine*, 48(11):2549–2575, 2018.

[57] Sarah da Glória Teles Bredt, Mauro Heleno Chagas, Gustavo Henrique Peixoto, Hans Joachim Menzel, and André Gustavo Pereira de Andrade. Understanding

Player Load: Meanings and Limitations. *Journal of Human Kinetics*, 71(1):5–9, 2020.

[58] Angel Gabriel Lucas-Cuevas, Alberto Encarnación-Martínez, Andrés Camacho-García, Salvador Llana-Belloch, and Pedro Pérez-Soriano. The location of the tibial accelerometer does influence impact acceleration parameters during running. *Journal of Sports Sciences*, 35(17):1734–1738, 2017.

[59] Kieran Moran, Amin Ahmadi, Chris Richter, Edmond Mitchell, Jennifer Kavanagh, and Noel O'Connor. Automatic detection, extraction, and analysis of landing during a training session, using a wearable sensor system. *Procedia Engineering*, 112:184–189, 2015.

[60] Christina Lyngsoe Udby, Franco M. Impellizzeri, Martin Lind, and Rasmus Østergaard Nielsen. How has workload been defined and how many workload-related exposures to injury are included in published sports injury articles? A scoping review. *Journal of Orthopaedic and Sports Physical Therapy*, 50(10):538–548, 2020.

[61] J.H. Ettema. Het model belasting en belastbaarheid. *T. Soc. Ceneesk.*, 51:44–54, 1973.

[62] Frank J.H. van Dijk, Max van Dormolen, Michiel A.J. Kompier, and Theo.F. Meijman. Herwaardering model belasting-belastbaarheid. *T. Soc. gezondheidsz.*, 68(1):3–10, 1990.

[63] Willem H. Meeuwisse. Assessing Causation in Sport Injury: A Multifactorial Model. *Clinical Journal of Sports Medicine*, 4(3):166–170, 1994.

[64] Willem H. Meeuwisse, Hugh Tyreman, Brent Hagel, and Carolyn Emery. A Dynamic Model of Etiology in Sport Injury: The Recursive Nature of Risk and Causation. *Clinical Journal of Sport Medicine*, 17(3):215–219, 2007.

[65] Natalia F.N. Bittencourt, Willem H. Meeuwisse, Luciana D. Mendonça, A. Nettel-Aguirre, Juliana M. Ocarino, and Sérgio T. Fonseca. Complex systems approach for sports injuries: Moving from risk factor identification to injury pattern recognition - Narrative review and new concept. *British Journal of Sports Medicine*, 50(21):1309–1314, 2016.

[66] Andrew S. McIntosh. Risk compensation, motivation, injuries, and biomechanics in competitive sport. *British Journal of Sports Medicine*, 39(1):2–3, 2005.

[67] W. Brent Edwards. Modeling Overuse Injuries in Sport as a Mechanical Fatigue Phenomenon. *Exercise and Sport Sciences Reviews*, 46(4):224–231, 2018.

[68] David B. Burr, R. Bruce Martin, Mitchell B. Schaffler, and Eric L. Radin. Bone remodeling in response to in vivo fatigue microdamage. *Journal of Biomechanics*, 18(3):189–200, 1985.

[69] Zeynep Seref-Ferlengez, Oran D. Kennedy, and Mitchell B. Schaffler. Bone microdamage, remodeling and bone fragility: how much damage is too much damage? *BoneKEy Reports*, 4(September 2014):1–7, 2015.

[70] Emily S. Matijevich, Leon R. Scott, Peter Volgyesi, Kendall H. Derry, and Karl E. Zelik. Combining wearable sensor signals, machine learning and biomechanics to estimate tibial bone force and damage during running. *Human Movement Science*, 74:102690, 2020.

[71] Michael L. Bertelsen, Adam Hulme, Jesper Petersen, René Børge K. Brund, Henrik Sørensen, Caroline F. Finch, Erik T. Parner, and Rasmus O. Nielsen. A framework for the etiology of running-related injuries. *Scandinavian Journal of Medicine and Science in Sports*, 27(11):1170–1180, 2017.

[72] Judd T. Kalkhoven, Mark L. Watsford, and Franco M. Impellizzeri. A conceptual model and detailed framework for stress-related, strain-related, and overuse athletic injury. *Journal of Science and Medicine in Sport*, 23(8):726–734, 2020.

[73] Laura Bowen, Aleksander Stefan Gross, Mo Gimpel, and François-Xavier Li. Accumulated workloads and the acute:chronic workload ratio relate to injury risk in elite youth football players. *British Journal of Sports Medicine*, 51(5):452–459, 2016.

[74] Rebecca Dennis, Patrick Farhart, C Goumas, and John Orchard. Bowling workload and the risk of injury in elite cricket fast bowlers. *Journal of Science and Medicine in Sport*, 6(3):359–367, 2003.

[75] Tim J. Gabbett and Shahid Ullah. Relationship between running loads and soft-tissue injury in elite team sport athletes. *Journal of strength and conditioning research*, 26:953–960, 2012.

[76] Sean Williams, Grant Trewartha, Simon P.T. Kemp, John H.M. Brooks, Colin W. Fuller, Aileen E. Taylor, Matthew J. Cross, Gavin Shaddick, and Keith A. Stokes. How Much Rugby is Too Much? A Seven-Season Prospective Cohort Study of Match Exposure and Injury Risk in Professional Rugby Union Players. *Sports Medicine*, 47(11):2395–2402, 2017.

[77] Nick B. Murray, Tim J. Gabbett, and Andrew D. Townshend. Relationship between preseason training load and in-season availability in elite australian football players. *International Journal of Sports Physiology and Performance*, 12(6):749–755, 2017.

[78] Billy T. Hulin, Tim J. Gabbett, Peter Blanch, Paul Chapman, David Bailey, and John W. Orchard. Spikes in acute workload are associated with increased injury risk in elite cricket fast bowlers. *British journal of sports medicine*, 48(8):708–712, 2014.

[79] John W. Orchard, Ffsem Uk, Trefor James, Marc Portus, Bhms Hon, Alex Kountouris, Bappsci Physio, Rebecca Dennis, and Bhlthsci Hon. Fast Bowlers in Cricket Demonstrate Up to 3- to 4-Week Delay Between High Workloads and Increased Risk of Injury. *The American Journal of Sports Medicine*, 37(6):1186–1192, 2009.

[80] Marcus J. Colby, Brian Dawson, Jarryd Heasman, Brent Rogalski, and Tim J. Gabbett. Accelerometer and GPS-derived running loads and injury risk in elite Australian footballers. *Journal of Strength and Conditioning Research*, 28(8):2244–2252, 2014.

[81] Shane Malone, Adam Owen, Matt Newton, Bruno Mendes, Kieran D. Collins, and Tim J. Gabbett. The acute:chonic workload ratio in relation to injury risk in professional soccer. *Journal of Science and Medicine in Sport*, 20(6):561–565, 2017.

[82] Matthew J. Cross, Sean Williams, Grant Trewartha, Simon P.T. Kemp, and Keith A. Stokes. The influence of in-season training loads on injury risk in professional rugby union. *International Journal of Sports Physiology and Performance*, 11(3):350–355, 2016.

[83] Tim J. Gabbett. Reductions in pre-season training loads reduce training injury rates in rugby league players. *British Journal of Sports Medicine*, 38(6):743–749, 2004.

[84] Timothy G. Eckard, Darin A. Padua, Darren W. Hearn, Brett S. Pexa, and Barnett S. Frank. The Relationship Between Training Load and Injury in Athletes: A Systematic Review. *Sports Medicine*, 48(8):1929–1961, 2018.

[85] Billy T. Hulin, Tim J. Gabbett, Daniel W. Lawson, Peter Caputi, and John A. Sampson. The acute:chronic workload ratio predicts injury: high chronic workload may decrease injury risk in elite rugby league players. *British Journal of Sports Medicine*, 50(4):231–236, 2016.

[86] Johann Windt, Tim J. Gabbett, Daniel Ferris, and Karim M. Khan. Training load–injury paradox: is greater preseason participation associated with lower in-season injury risk in elite rugby league players? *British Journal of Sports Medicine*, 51(8):645–650, 2017.

[87] Marienke Van Middelkoop, Jelle Kolkman, John M. Van Ochten, Sita M.A. Bierma-Zeinstra, and Bart W. Koes. Risk factors for lower extremity injuries among male marathon runners. *Scandinavian Journal of Medicine and Science in Sports*, 18(6):691–697, 2008.

[88] Shane Malone, Adam Owen, Bruno Mendes, Brian Hughes, Kieran Collins, and Tim J. Gabbett. High-speed running and sprinting as an injury risk factor in soccer: Can well-developed physical qualities reduce the risk? *Journal of Science and Medicine in Sport*, 21(3):257–262, 2018.

[89] Brent Rogalski, Brian Dawson, Jarryd Heasman, and Tim J. Gabbett. Training and game loads and injury risk in elite Australian footballers. *Journal of Science and Medicine in Sport*, 16(6):499–503, 2013.

[90] Rasmus Østergaard Nielsen, Erik Thorlund Parner, Ellen Aagaard Nohr, Henrik Sørensen, Martin Lind, and Sten Rasmussen. Excessive progression in weekly running distance and risk of running-related injuries: An association which varies ac-

cording to type of injury. *Journal of Orthopaedic and Sports Physical Therapy*, 44(10):739–747, 2014.

[91] Amby Burfoot. The 10-Percent Rule. https://www.runnersworld.com/training/a20781512/the-10-percent-rule/, 2001. Date accessed: 2021-08-13.

[92] Rebecca Johansson. A New Approach to the 10 Percent Rule. https://www.trainingpeaks.com/blog/a-new-approach-to-the-10-percent-rule/. Date accessed: 2021-08-13.

[93] Eric W. Banister, Thomas W. Calvert, Margaret V. Savage, and Tim Bach. A systems model of training for athletic performance. *Australian Journal of Sports Medicine*, 7:57–61, 1975.

[94] Franco M. Impellizzeri, Patrick Ward, Aaron J. Coutts, Luke Bornn, and Alan Mccall. Training load and injury: part 2. Questionable research practices hijack the truth and mislead well-intentioned clinicians. *Journal of Orthopaedic & Sports Physical Therapy*, 50(10):577–584, 2021.

[95] Franco M. Impellizzeri, Patrick Ward, Aaron J. Coutts, Luke Bornn, and Alan Mccall. Training load and injury: part 1. The devil is in the detail – challenges to applying the current research in the training load and injury field. *Journal of Orthopaedic & Sports Physical Therapy*, 50(10):574–576, 2020.

[96] Norbert Kerr. HARKing: Hypothesizing After the Results are Known. *Personality and Social Psychology Review*, 2(3):196–217, 1998.

[97] Rasmus Oestergaard Nielsen, Michael Lejbach Bertelsen, Daniel Ramskov, Merete Møller, Adam Hulme, Daniel Theisen, Caroline F. Finch, Lauren Victoria Fortington, Mohammad Ali Mansournia, and Erik Thorlund Parner. Time-to-event analysis for sports injury research part 2: Time-varying outcomes. *British Journal of Sports Medicine*, 53(1):70–78, 2019.

[98] Johann Windt, Clare L. Ardern, Tim J. Gabbett, Karim M. Khan, Chad E. Cook, Ben C. Sporer, and Bruno D. Zumbo. Getting the most out of intensive longitudinal data : a methodological review of workload – injury studies. *BMJ Open*, 8(10):e022626, 2018.

[99] Guowei Li, Monica Taljaard, Edwin R. Van Den Heuvel, Mitchell A.H. Levine, Deborah J. Cook, George A. Wells, Philip J. Devereaux, and Lehana Thabane. An introduction to multiplicity issues in clinical trials: The what, why, when and how. *International Journal of Epidemiology*, 46(2):746–756, 2017.

[100] Luke Bornn, Patrick Ward, and Darcy Norman. Training Schedule Confounds the Relationship between Acute:Chronic Workload Ratio and Injury. *MIT Sloan Sports Analytics Conference*, pages 1–5, 2019.

[101] David L. Carey, Kay M. Crossley, Rod Whiteley, Andrea Mosler, Kok Leong Ong, Justin Crow, and Meg E. Morris. Modeling Training Loads and Injuries: The Dangers of Discretization. *Medicine and Science in Sports and Exercise*, 50(11):2267–2276, 2018.

[102] Howard Wainer, Marc Gessaroli, and Monica Verdi. Visual Revelations. Finding What Is Not There through the Unfortunate Binning of Results: The Mendel Effect. *CHANCE*, 19(1):49–52, 2006.

[103] Sander Greenland. Dose-response and trend analysis in epidemiology: alternatives to categorical analysis. *Epidemiology*, 6(4):356–365, 1995.

[104] Douglas Curran-Everett. Explorations in statistics: The analysis of ratios and normalized data. *American Journal of Physiology - Advances in Physiology Education*, 37(3):213–219, 2013.

[105] Lorenzo Lolli, Alan M. Batterham, Richard Hawkins, David M. Kelly, Anthony J. Strudwick, Robin T. Thorpe, Warren Gregson, and Greg Atkinson. The acute-to-chronic workload ratio: An inaccurate scaling index for an unnecessary normalisation process? *British Journal of Sports Medicine*, 53(24):1510–1512, 2019.

[106] Lorenzo Lolli, Alan M. Batterham, Richard Hawkins, David M. Kelly, Anthony J. Strudwick, Robin Thorpe, Warren Gregson, and Greg Atkinson. Mathematical coupling causes spurious correlation within the conventional acute-to-chronic workload ratio calculations. *British journal of sports medicine*, 53(15):921–922, 2019.

[107] Julie Ferrell-Olson. Transitioning Back Into the Studio: Periodization for Dance. https://www.apollaperformance.com/blogs/news/transitioning-back-into-the-studio-periodization-for-dance, 2020. Date accessed: 2021-08-24.

[108] Matthew A. Wyon. Preparing to perform: periodization and dance. *Journal of Dance Medicine & Science*, 14(2):67–72, 2010.

[109] Annie C. Jeffries, Lee W. Wallace, and Aaron J. Coutts. Quantifying Training Loads in Contemporary Dance. *International Journal of Sports Physiology and Performance*, 12(6):796–802, 2016.

[110] Brenton Surgenor and Matthew A. Wyon. Measuring Training Load in Dance: The Construct Validity of Session-RPE. *Medical Problems of Performing Artists*, 34(1):1–5, 2019.

[111] Valeriya G. Volkova, Amanda M. Black, and Sarah J. Kenny. Internal Training Load Measures in Elite Adolescent Ballet Dancers. *Journal of Dance Medicine & Science*, 24(4):175–182, 2020.

[112] Thomas Gus Almonroeder, Lauren Benson, Alexandra Madigan, Drake Everson, Cameron Buzzard, Madison Cook, and Brian Henriksen. Exploring the potential utility of a wearable accelerometer for estimating impact forces in ballet dancers. *Journal of Sports Sciences*, 38(2):231–237, 2020.

[113] Danica Hendry, Ryan Leadbetter, Kristoffer McKee, Luke Hopper, Catherine Wild, Peter O'sullivan, Leon Straker, and Amity Campbell. An exploration of machine-learning estimation of ground reaction force from wearable sensor data. *Sensors*, 20(3):740, 2020.

[114] Danica Hendry, Kevin Chai, Amity Campbell, Luke Hopper, Peter O'Sullivan, and Leon Straker. Development of a Human Activity Recognition System for Ballet Tasks. *Sports Medicine - Open*, 6(1), 2020.

[115] Chris Michael Brogden, Ross Armstrong, Richard Page, Debbie Milner, Debbie Norris, and Matt Greig. Use of Triaxial Accelerometry During the Dance Aerobic Fitness Test: Considerations for Unit Positioning and Implications for Injury Risk and Performance. *Journal of Dance Medicine & Science*, 2(3):115–122, 2018.

[116] Emma Redding, Peter Weller, Shantel Ehrenberg, Sarah Irvine, Edel Quin, Sonia Rafferty, Matthew Wyon, and Carol Cox. The Development of a High Intensity Dance Performance Fitness Test. *Journal of dance medicine & science*, 13(1):3–9, 2009.

[117] Emily S. Matijevich, Lauren M. Branscombe, Leon R. Scott, and Karl E. Zelik. Ground reaction force metrics are not strongly correlated with tibial bone load when running across speeds and slopes: Implications for science, sport and wearable tech. *PLoS ONE*, 14(1):1–19, 2019.

[118] Ann Bowling. Injuries to dancers: Prevalence, treatment, and perceptions of causes. *British Medical Journal*, 298(6675):731–734, 1989.

[119] Peter Brinson and Fiona Dick. Fit to Dance? The Report of the National Inquiry into Dancers' Health and Injury. Technical report, 1996.

[120] Peta Blevins, Shona Erskine, Luke Hopper, and Gene Moyle. Finding Your Balance: An Investigation of Recovery–Stress Balance in Vocational Dance Training. *Journal of Dance Education*, 20(1):12–22, 2020.

[121] Annie C. Jeffries, Lee Wallace, Aaron J. Coutts, Ashlea M. Cohen, Alan Mccall, and Franco M. Impellizzeri. Injury, Illness, and Training Load in a Professional Contemporary Dance Company: A Prospective Study. *Journal of Athletic Training*, 55(9):967–976, 2020.

[122] Jeske R.E. Boeding, Edwin Visser, Duncan E. Meuffels, and Robert-Jan de Vos. Is Training Load Associated with Symptoms of Overuse in Dancers? A Prospective Observational Study. *Journal of Dance Medicine & Science*, 23(1):11–17, 2019.

[123] Roisin Cahalan, Philip Kearney, Orfhlaith Ni Bhriain, Emma Redding, Edel Quin, Lisa C. McLaughlin, and Kieran O' Sullivan. Dance exposure, wellbeing and injury in collegiate Irish and contemporary dancers: A prospective study. *Physical Therapy in Sport*, 34:77–83, 2018.

[124] J. Fernandez, A. Mendez-Villanueva, and B.M. Pluim. Intensity of tennis match play. *British Journal of Sports Medicine*, 40(5):387–391, 2006.

[125] Jerald L. Cohen, Karen R. Segal, and William D. Mcardle. Heart Rate Response to Ballet Stage Performance. *The Physician and Sportsmedicine*, 10(11):120–133, 1982.

[126] John W. Orchard, Trefor James, Errol Alcott, S. Carter, and Patrick Farhart. Injuries in Australian cricket at first class level 1995/1996 to 2000/2001: Commentary. *British Journal of Sports Medicine*, 36(4):275, 2002.

[127] Richard D. Hawkins and Colin W. Fuller. A prospective epidemiological study of injuries in four English professional football clubs. *British Journal of Sports Medicine*, 33(3):196–203, 1999.

[128] D.G. Allen, G.D. Lamb, and H. Westerblad. Skeletal muscle fatigue: cellular mechanisms. *Physiological reviews*, 88(1):287–332, 2008.

[129] Ross Armstrong and Nicola Relph. Screening Tools as a Predictor of Injury in Dance: Systematic Literature Review and Meta-analysis. *Sports Medicine - Open*, 4(33), 2018.

[130] Jeffrey A. Russell. Preventing dance injuries: current perspectives. *Open Access Journal of Sports Medicine*, (4):199–210, 2013.

[131] David Moher, Alessandro Liberati, Jennifer Tetzlaff, and Douglas G. Altman. Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *BMJ*, 339(b2535), 2009.

[132] Ankit Rohatgi. WebPlotDigitizer v. 4.3. https://apps.automeris.io/wpd/, 2020. Date accessed: 2020-08-12.

[133] Quan Nha Hong, Sergi Fàbregues, Gillian Bartlett, Felicity Boardman, Margaret Cargo, Pierre Dagenais, Marie Pierre Gagnon, Frances Griffiths, Belinda Nicolau, Alicia O'Cathain, Marie Claude Rousseau, Isabelle Vedel, and Pierre Pluye. The Mixed Methods Appraisal Tool (MMAT) version 2018 for information professionals and researchers. *Education for Information*, 34(4):285–291, 2018.

[134] Sara H. Downs and Nick Black. The feasibility of creating a checklist for the assessment of the methodological quality both of randomised and non-randomised studies of health care interventions. *Journal of Epidemiology and Community Health*, 52(6):377–384, 1998.

[135] Phil Hooper, Jeffrey W. Jutai, Graham Strong, and Elizabeth Russell-Minda. Age-related macular degeneration and low-vision rehabilitation: a systematic review. *Canadian Journal of Opthalmology*, 43(2):180–187, 2008.

[136] Jerald L. Cohen, Karen R. Segal, Ira Witriol, and William D. McArdle. Cardiorespiratory responses to ballet exercise and the VO2max of elite ballet dancers. *Medicine & Science in Sports & Exercise*, 14(3):212–217, 1982.

[137] Emily Twitchett, Manuela Angioi, Yiannis Koutedakis, and Matthew A. Wyon. Video Analysis of Classical Ballet Performance. *Journal of Dance Medicine & Science*, 13(4):124–8, 2009.

[138] Michelle S.S. Costa, Arthur S. Ferreira, Marco Orsini, Elirez B. Silva, and Lilian Ramiro Felicio. Characteristics and prevalence of musculoskeletal injury in professional and non-professional ballet dancers. *Brazilian Journal of Physical Therapy*, 20(2):166–175, 2016.

[139] Ashley F. Doyle-Lucas, Jeremy D. Akers, and Brenda M. Davy. Energetic Efficiency, Menstrual Irregularity, and Bone Mineral Density in Elite Professional Female Ballet Dancers. *Journal of Dance Medicine & Science*, 14(4):146–155, 2010.

[140] Soo Youn Kim, Jung Ho Cho, Ji Hyun Lee, and Jae Hyun Jung. Changes in Body Composition, Energy Metabolism, and Appetite-Regulating Hormones in Korean Professional Female Ballet Dancers Before and After Ballet Performance. *Journal of Dance Medicine & Science*, 23(4):173–180, 2019.

[141] Andrea C. Kozai, Emily Twitchett, Sian Morgan, and Matthew A. Wyon. Workload Intensity and Rest Periods in Professional Ballet: Connotations for Injury. *International Journal of Sports Medicine*, 41(6):373–379, 2020.

[142] Emily Twitchett, Manuela Angioi, Yiannis Koutedakis, and Matthew A. Wyon. The Demands of a Working Day Among Female Professional Ballet Dancers. *Journal of Dance Medicine & Science*, 14(4):127–132, 2010.

[143] Matthew A. Wyon, Nick Allen, Manuela Angioi, Alan Nevill, and Emily Twitchett. Anthropometric Factors Affecting Vertical Jump Height in Ballet Dancers. *Journal of Dance Medicine & Science*, 10(3 & 4):106–110, 2006.

[144] Matthew A. Wyon, Martine A. Deighan, Alan M. Nevill, Michael Doherty, Sharon L. Morrison, Nick Allen, Simon J. Jobson, and Simon George. The cardiorespiratory, anthropometric, and performance characteristics of an international/national touring ballet company. *Journal of Strength and Conditioning Research*, 21(2):389–393, 2007.

[145] V. Seliger, J. Glücksmann, J. Pachlopník, and I. Pachlopníková. Evaluation of stage artist's activities on basis of telemetrical measurements of heart rates. *Internationale Zeitschrift für Angewandte Physiologie Einschließlich Arbeitsphysiologie*, 28(2):86–104, 1970.

[146] Donald T. Kirkendall, John A. Bergfeld, Leonard Calabrese, J A Lombardo, G M Street, and Garron G Weiker. lsokinetic Characteristics of Ballet Dancers and the Response to a Season of Ballet Training. *Journal of Orthopaedic & Sports Physical Therapy*, 5(4):207–211, 1984.

[147] Yiannis Koutedakis, Lynne Myszkewycz, Dimitrios Soulas, V. Papapostolou, I. Sullivan, and N.C. Craig Sharp. The Effects of Rest and Subsequent Training on Selected Physiological Parameters in Professional Female Classical Dancers. *International Journal of Sports Medicine*, 20(6):379–383, 1999.

[148] Lyle J. Micheli, Michelina Cassella, Avery D. Faigenbaum, Heather Southwick, and Vanessa Ho. Preseason to Postseason Changes in Body Composition of Professional Ballet Dancers. *Journal of Dance Medicine & Science*, 9(2):56–59, 2005.

[149] Eva Ramel, Ola Thorsson, and Per Wollmer. Fitness training and its effect on musculoskeletal pain in professional ballet dancers. *Scandinavian Journal of Medicine and Science in Sports*, 7(5):293–298, 1997.

[150] Matthew A. Wyon, Yiannis Koutedakis, Roger Wolman, Alan M. Nevill, and Nick Allen. The influence of winter vitamin D supplementation on muscle function and injury occurrence in elite ballet dancers: A controlled study. *Journal of Science and Medicine in Sport*, 17(1):8–12, 2014.

[151] Yiannis Koutedakis and N.C. Craig Sharp. Thigh-muscles strength training, dance exercise, dynamometry, and anthropometry in professional ballerinas. *Journal of Strength and Conditioning Research*, 18(4):714–718, 2004.

[152] Lucas Maciel Rabello, Johannes Zwerver, Roy E. Stewart, Inge van den Akker-Scheek, and Michel S. Brink. Patellar tendon structure responds to load over a 7-week preseason in elite male volleyball players. *Scandinavian Journal of Medicine and Science in Sports*, 29(7):992–999, 2019.

[153] Aaron T. Scanlan, Ben J. Dascombe, Andrew P. Kidcaff, Jessica L. Peucker, and Vincent J. Dalbo. Gender-specific activity demands experienced during semiprofessional basketball game play. *International Journal of Sports Physiology and Performance*, 10(5):618–625, 2015.

[154] Layla R. Moran, Eric J. Hegedus, Chris M. Bleakley, and Jeffrey B. Taylor. Jump load: Capturing the next great injury analytic. *British Journal of Sports Medicine*, 53(1):8–9, 2019.

[155] John H.M. Brooks, Colin W. Fuller, Simon P.T. Kemp, and Dave B. Reddin. An assessment of training volume in professional rugby union and its impact on the incidence, severity, and nature of match and training injuries. *Journal of Sports Sciences*, 26(8):863–873, 2008.

[156] Diane M. Dellavalle and Jere D. Haas. Quantification of training load and intensity in female collegiate rowers: Validation of a daily assessment tool. *Journal of Strength and Conditioning Research*, 27(2):540–548, 2013.

[157] Joseph W. Shaw, Matthew Springham, Derrick D. Brown, Adam M. Mattiussi, Charles R. Pedlar, and Jamie Tallent. The Validity of the Session Rating of Perceived Exertion Method for Measuring Internal Training Load in Professional Classical Ballet Dancers. *Frontiers in Physiology*, 2020.

[158] Carla Cristiane Da Silva, Tamara Beres Lederer Goldberg, Lúcio Flávio Soares-Caldeira, Ricardo Dos Santos Oliveira, Solange De Paula Ramos, and Fábio Yuzo Nakamura. The Effects of 17 Weeks of Ballet Training on the Autonomic Modulation, Hormonal and General Biochemical Profile of Female Adolescents. *Journal of Human Kinetics*, 47(1):61–71, 2015.

[159] Mark S. Kovacs, Robert Pritchett, P. Jason Wickwire, J. Matthew Green, and Phillip Bishop. Physical performance changes after unsupervised training during the autumn/spring semester break in competitive tennis players. *British Journal of Sports Medicine*, 41(11):705–710, 2007.

[160] Yiannis Koutedakis, Richard Budgett, and Leopold Faulmann. Rest in underperforming elite competitors. *British Journal of Sports Medicine*, 24(4):248–252, 1990.

[161] Nina T. Frusztajer, Sarita Dhuper, Michelle P. Warren, J. Brooks-Gunn, and Richard P. Fox. Nutrition and the incidence of stress fractures in ballet dancers. *American Journal of Clinical Nutrition*, 51(5):779–83, 1990.

[162] Margo Mountjoy, Jorunn Sundgot-Borgen, Louise Burke, Susan Carter, Naama Constantini, Constance Lebrun, Nanna Meyer, Roberta Sherman, Kathrin Steffen, Richard Budgett, and Arne Ljungqvist. The IOC consensus statement: Beyond the Female Athlete Triad-Relative Energy Deficiency in Sport (RED-S). *British Journal of Sports Medicine*, 48(7):491–497, 2014.

[163] Adam Mattiussi, Joseph W. Shaw, Derrick D. Brown, Phil Price, Daniel D. Cohen, Charles R. Pedlar, and Jamie Tallent. Jumping in Ballet A Systematic Review of Kinetic and Kinematic Parameters. *Medical Problems of Performing Artists*, 36(2):108–128, 2021.

[164] Jeffrey A. Russell. Insights into the Position of the Ankle and Foot in Female Ballet Dancers En Pointe. *The IADMS Bulletin for Dancers and Teachers*, 6(1):10–12, 2015.

[165] Melanie Fuller, Gene M. Moyle, Andrew P. Hunt, and Geoffrey M. Minett. Ballet and Contemporary Dance Injuries When Transitioning to Full-Time Training or Professional Level Dance: A Systematic Review. *Journal of Dance Medicine & Science : official publication of the International Association for Dance Medicine & Science*, 23(3):112–125, 2019.

[166] Daphne E. Karreman, Stephanie C. Keizer-Hulsebosch, and Janine H. Stubbe. Performing artist and Athlete Health Monitor: User experience, content and conditions for use of an online dance-health surveillance system in a professional ballet company. *BMJ Open Sport and Exercise Medicine*, 5(1):16–18, 2019.

[167] Shaw Bronner, Sheyi Ojofeitimi, Jennifer Bailey Lora, Heather Southwick, Michelina Cassella Kulak, Jennifer Gamboa, Megan Rooney, Greg Gilman, and Richard Gibbs. A Preseason Cardiorespiratory Profile of Dancers in Nine Professional Ballet and Modern Companies. *Journal of Dance Medicine & Science*, 18(2):74–85, 2014.

[168] Laurent Bosquet, Jonathan Montpetit, Denis Arvisais, and Iñigo Mujika. Effects of tapering on performance: A meta-analysis. *Medicine and Science in Sports and Exercise*, 39(8):1358–1365, 2007.

[169] Linda Lee, Duncan Reid, Jill Cadwell, and Priya Palmer. Injury incidence , dance exposure and the use of the movement competency screen (MCS) to full-time pre- professional dancers. *The International Journal of Sports Physical Therapy*, 12(3):352–370, 2017.

[170] Jan P. Vandenbroucke, Erik von Elm, Douglas G. Altman, Peter C. Gøtzsche, Cynthia D. Mulrow, Stuart J. Pocock, Charles Poole, James J. Schlesselman, Matthias Egger, Maria Blettner, Paolo Boffetta, Hermann Brenner, Genevie've Chêne, Cyrus Cooper, George Davey-Smith, France Gagnon, Philip Greenland, Sander Greenland, Claire Infante-Rivard, John Ioannidis, Astrid James, Giselle Jones, Bruno Ledergerber, Julian Little, Margaret May, David Moher, Hooman Momen, Alfredo Morabia, Hal Morgenstern, Fred Paccaud, Martin Röösli, Dietrich Rothenbacher, Kenneth Rothman, Caroline Sabin, Willi Sauerbrei, Lale Say, Jonathan Sterne, Holly Syddall, Ian White, Susan Wieland, Hywel Williams, and Guang Yong Zou. Strengthening the Reporting of Observational Studies in Epidemiology (STROBE): Explanation and elaboration. *International Journal of Surgery*, 12(12):1500–1524, 2014.

[171] Roald Bahr, Ben Clarsen, Wayne Derman, Jiri Dvorak, Carolyn A. Emery, Caroline F. Finch, Martin Hägglund, Astrid Junge, Simon Kemp, Karim M. Khan, Stephen W. Marshall, Willem Meeuwisse, Margo Mountjoy, and John W. Orchard. International Olympic Committee consensus statement: methods for recording and reporting of epidemiological data on injury and illness in sport 2020 (including STROBE Extension for Sport Injury and Illness Surveillance (STROBE-SIIS)). *British Journal of Sports Medicine*, 54:372–389, 2020.

[172] Lluís Til, John Orchard, and Katherine Rae. The orchard sports injury classification system (OSICS) version 10. *Apunts Medicina de l'Esport*, 43(159):109–112, 2008.

[173] Benjamin Clarsen and Roald Bahr. Matching the choice of injury/illness definition to study setting, purpose and design: One size does not fit all! *British Journal of Sports Medicine*, 48(7):510–512, 2014.

[174] Colin W. Fuller, Jan Ekstrand, Astrid Junge, Thor E. Andersen, Roald Bahr, Jiri Dvorak, Martin Hägglund, Paul McCrory, and Willem H. Meeuwisse. Consensus statement on injury definitions and data collection procedures in studies of football (soccer) injuries. *British Journal of Sports Medicine*, 40(3):193–201, 2006.

[175] Colin W. Fuller, Michael G. Molloy, Christian Bagate, Roald Bahr, John H.M. Brooks, Hilton Donson, Simon P.T. Kemp, Paul McCrory, Andrew S. McIntosh, Willem H. Meeuwisse, Kenneth L. Quarrie, Martin Raftery, and Preston Wiley. Consensus statement on injury definitions and data collection procedures for studies of injuries in rugby union. *British Journal of Sports Medicine*, 41(5):328–331, 2007.

[176] Karen G. Roos and Stephen W. Marshall. Definition and usage of the term "overuse injury" in the us high school and collegiate sport epidemiology literature: A systematic review. *Sports Medicine*, 44(3):405–421, 2014.

[177] Marijeanne Liederbach, Marshall Hagins, Jennifer M. Gamboa, and Thomas M. Welsh. Assessing and Reporting Dancer Capacities, Risk Factors, and Injuries: Recommendations from the IADMS Standard Measures Consensus Initiative. *Journal of Dance Medicine & Science*, 16(4):139–153, 2012.

[178] Sunil Kappal. Data Normalization using Median & Median Absolute Deviation (MMAD) based Z-Score for Robust Predictions vs. Min-Max Normalization. *London Journal of Research in Science: Natural and Formal Volume*, 19(4):39–44, 2019.

[179] Martin Hägglund, Markus Waldén, and Jan Ekstrand. Previous injury as a risk factor for injury in elite football: A prospective study over two consecutive seasons. *British Journal of Sports Medicine*, 40(9):767–772, 2006.

[180] Sarah J. Kenny, Jackie L. Whittaker, and Carolyn A. Emery. Risk factors for musculoskeletal injury in preprofessional dancers: A systematic review. *British Journal of Sports Medicine*, 50(16):997–1003, 2016.

[181] John W. Orchard. Intrinsic and Extrinsic Risk Factors for Muscle Strains in Australian Football. *American Journal of Sports Medicine*, 29(3):300–303, 2001.

[182] Terry Therneau. A Package for Survival Analysis in R. https://cran.r-project.org/package=survival, 2020.

[183] P. Peduzzi, J. Concato, A.R. Feinstein, and T.R. Holford. Importance of events per independent variable in proportional hazards regression analysis II. *Journal of Clinical Epidemiology*, 48(12):1503–1510, 1995.

[184] Peter C. Austin, Douglas S. Lee, and Jason P. Fine. Introduction to the Analysis of Survival Data in the Presence of Competing Risks. *Circulation*, 133(6):601–609, 2016.

[185] Tim J. Gabbett, Shahid Ullah, and Caroline F. Finch. Identifying risk factors for contact injury in professional rugby league players - Application of a frailty model for recurrent injury. *Journal of Science and Medicine in Sport*, 15(6):496–504, 2012.

[186] Christopher Gandrud. simPH: An R package for illustrating estimates from cox proportional hazard models including for interactive and nonlinear effects. *Journal of Statistical Software*, 65(3):1–20, 2015.

[187] Rasmus Oestergaard Nielsen, Michael Lejbach Bertelsen, Daniel Ramskov, Merete Møller, Adam Hulme, Daniel Theisen, Caroline F. Finch, Lauren Victoria Fortington, Mohammad Ali Mansournia, and Erik Thorlund Parner. Time-to-event analysis for sports injury research part 1: Time-varying exposures. *British Journal of Sports Medicine*, 53(1):61–68, 2019.

[188] Anna Warren, Sean Williams, Steve McCaig, and Grant Trewartha. High acute:chronic workloads are associated with injury in England & Wales Cricket Board Development Programme fast bowlers. *Journal of Science and Medicine in Sport*, 21(1):40–45, 2018.

[189] Ethan R. Wiesler, D. Monte Hunter, David F. Martin, Walton W. Curl, and Helena Hoen. Ankle Flexibility and Injury Patterns in Dancers. *The American Journal of Sports Medicine*, 24(6):754–757, 1996.

[190] David M. Swenson, Ellen E. Yard, Sarah K. Fields, and R. Dawn Comstock. Patterns of recurrent injuries among US high school athletes, 2005-2008. *American Journal of Sports Medicine*, 37(8):1586–1593, 2009.

[191] Craig L. Jacobs, J. David Cassidy, Pierre Côté, Eleanor Boyle, Eva Ramel, Carlo Ammendolia, Jan Hartvigsen, and Isabella Schwartz. Musculoskeletal Injury in Professional Dancers : Prevalence and Associated Factors . An International Cross-sectional Study by Musculoskeletal Injury in Professional Dancers : Prevalence and Associated Factors . An International Cross-sectional Study. *Clinical Journal of Sport Medicine*, 27(2):153–160, 2017.

[192] Luís Xarez, Fernando Pereira, and Gonçalo Mendonça. Monitoring work and rest during performance and life-style: A study case with a principal ballet dancer. In *Proceedings of the International Symposium on Performance Science*, pages 537–542, 2009.

[193] Philip Sedgwick. Retrospective cohort studies: Advantages and disadvantages. *BMJ*, 348(January):1–2, 2014.

[194] William J. Kraemer, Brett Comstock, James E. Clark, and Courtenay Dunn-Lewis. Athlete needs analysis. In Jay Hoffman, editor, *NSCA's Guide to Program Design*, chapter 1, pages 1–21. Human Kinetics, 1 edition, 2012.

[195] Michael A. Christmass, Susan E. Richmond, Nigel T. Cable, Peter G. Arthur, and Peter E. Hartmann. Exercise intensity and metabolic response in singles tennis. *Journal of Sports Sciences*, 16(8):739–747, 1998.

[196] Romain Meeusen, Martine Duclos, Carl Foster, Andrew Fry, Michael Gleeson, David Nieman, John Raglin, Gerard Rietjens, Jürgen Steinacker, and Axel Urhausen. Prevention, diagnosis and treatment of the overtraining syndrome: Joint consensus statement of the European College of Sport Science (ECSS) and the American College of Sports Medicine (ACSM). *European Journal of Sport Science*, 13(1):1–24, 2013.

[197] Asier Los Arcos, Raul Martínez-Santos, Javier Yanci, Jurdan Mendiguchia, and Alberto Méndez-Villanueva. Negative Associations between Perceived Training Load, Volume and Changes in Physical Fitness in Professional Soccer Players Negative Associations between Perceived Training Load, Volume and Changes in Physical

Fitness in Professional Soccer Players. *Journal of Sports Science and Medicine*, 14(2):394–401, 2015.

[198] Asier Los Arcos, Raúl Martínez-Santos, Yanci Javier, and Alberto Mendez-Villanueva. Monitoring Perceived Respiratory and Muscular Exertions and Physical Fitness in Young Professional Soccer Players During a 32-Week Period. *Kinesiology*, 49(2):153–160, 2017.

[199] Joseph W. Shaw, Adam M. Mattiussi, Derrick D. Brown, Sean Williams, Shane Kelly, Matthew Springham, Charles R. Pedlar, and Jamie Tallent. Dance Exposure, Individual Characteristics, and Injury Risk over Five Seasons in a Professional Ballet Company. *Medicine & Science in Sports & Exercise*, 2021.

[200] Douglas Bates, Martin Maechler, Ben Bolker, Steven Walker, Rune Haubo Bojesen Christensen, Henrik Singmann, Bin Dai, Fabian Scheipl, Gabor Grothendieck, Peter Green, and John Fox. Linear mixed-effects model using 'Eigen' and S4. 2020.

[201] L.J.M. Vermulst, Cees Vervoorn, Anne-Marie Boelens-Quist, Hans P.F. Koppeschaar, Wietze B.M. Erich, J. H.H. Thijssen, and Wouter R. De Vries. Analysis of seasonal training volume and working capacity in elite female rowers. *International Journal of Sports Medicine*, 12(6):567–572, 1991.

[202] Jenny Jacobsson, Toomas Timpka, Jan Kowalski, Sverker Nilsson, Joakim Ekberg, Örjan Dahlström, and Per A Renström. Injury patterns in Swedish elite athletics: annual incidence, injury types and risk factors. *British Journal of Sports Medicine*, 47(15):986–991, 2013.

[203] Yiannis Koutedakis. "Burnout" in Dance: The Physiological Viewpoint. *Journal of Dance Medicine & Science*, 4(4):122–127, 2000.

[204] Paula C. Charlton, Dan Ilott, Russell Borgeaud, and Michael K. Drew. Risky business: An example of what training load data can add to shared decision making in determining 'acceptable risk'. *Journal of Science and Medicine in Sport*, 20(6):526–527, 2017.

[205] Melanie Fuller, Gene M. Moyle, and Geoffrey M. Minett. Injuries across a pre-professional ballet and contemporary dance tertiary training program: A retrospective cohort study. *Journal of Science and Medicine in Sport*, 23(12):1166–1171, 2020.

[206] Melanie Fuller, Gene M. Moyle, Andrew P. Hunt, and Geoffrey M. Minett. Injuries during transition periods across the year in pre-professional and professional ballet and contemporary dancers: A systematic review and meta-analysis. *Physical Therapy in Sport*, 44:14–23, 2020.

[207] Jan Ekstrand, Martin Hägglund, and Markus Waldén. Epidemiology of muscle injuries in professional football (soccer). *American Journal of Sports Medicine*, 39(6):1226–1232, 2011.

[208] Sandra Mårtensson, Kristina Nordebo, and Christer Malm. High Training Volumes are Associated with a Low Number of Self-Reported Sick Days in Elite Endurance Athletes. *Journal of Sports Science and Medicine*, 13(4):929–933, 2014.

[209] Johnny Padulo, Helmi Chaabène, Montassar Tabben, Monoem Haddad, Cecilia Gevat, Stefano Vando, Lucio Maurino, Anis Chaouachi, and Karim Chamari. The construct validity of session RPE during an intensive camp in young male Karate athletes. *Muscles, Ligaments and Tendons Journal*, 4(2):121–126, 2014.

[210] Ali Ozkan and Ayse Kin-Isler. The reliability and validity of regulating exercise intensity by ratings of perceived exertion in step dance sessions. *Journal of Strength and Conditioning Research*, 21(1):296–300, 2007.

[211] Corrado Lupo, Laura Capranica, Cristina Cortis, Flavia Guidotti, Antonino Bianco, and Antonio Tessitore. Session-RPE for quantifying load of different youth taekwondo training sessions. *The Journal of sports medicine and physical fitness*, 57(3):189–194, 2017.

[212] Corrado Lupo, Antonio Tessitore, Lorenzo Gasperi, and M.A.R. Gomez. Session-RPE for quantifying the load of different youth basketball training sessions. *Biology of Sport*, 34(1):11–17, 2017.

[213] Do-Yeon Kim and Jeong-Ah Lee. Gender Comparison of Ratings of Perceived Exertion (RPE) as a Predictor of Exercise Intensity in College Students. *Journal of Life Science*, 21(1):9–14, 2011.

[214] Kyle R. Barnes. Comparisons of Perceived Training Doses in Champion Collegiate-Level Male and Female Cross-country Runners and Coaches over the Course of a Competitive Season. *Sports Medicine - Open*, 3(38):1–9, 2017.

[215] Carol C. Teitz, Richard M. Harrington, and Hannah Wiley. Pressures on the Foot in Pointe Shoes. *Foot & Ankle International*, 5(5):216–221, 1985.

[216] Eric W. Banister. Modeling Elite Athletic Performance. In H. Green, J. McDougal, and H. Wenger, editors, *Modeling Elite Athletic Performance*, pages 403–424. Human Kinetics, Champaign, IL, 1991.

[217] Corrado Lupo, Laura Capranica, and Antonio Tessitore. The validity of the session-RPE method for quantifying training load in water polo. *International Journal of Sports Physiology and Performance*, 9(4):656–660, 2014.

[218] Hirofumi Tanaka, Kevin D. Monahan, and Douglas R. Seals. Age-predicted maximal heart rate revisited. *Journal of the American College of Cardiology*, 37(1):153–156, 2001.

[219] Joshua Christen, Carl Foster, John P. Porcari, and Richard P. Mikat. Temporal Robustness of the Session Rating of Perceived Exertion. *International journal of sports physiology and performance*, 11(8):1088–1093, nov 2016.

[220] Maurizio Fanchini, Ivan Ferraresi, Andrea Petruolo, Andrea Azzalin, Roberto Ghielmetti, Federico Schena, and Franco M. Impellizzeri. Is a retrospective RPE appropriate in soccer? Response shift and recall bias. *Science and Medicine in Football*, 1(1):53–59, 2017.

[221] Anthony J. Bishara and James B. Hittner. Testing the significance of a correlation with nonnormal data: Comparison of Pearson, Spearman, transformation, and resampling approaches. *Psychological Methods*, 17(3):399–417, 2012.

[222] J. Martin Bland and Douglas G. Altman. Calculating Correlation coefficients with repeated observations: Part 1—correlation within subjects. *BMJ*, 310(6977):446, 1995.

[223] Jonathan Z. Bakdash and Laura R. Marusich. Repeated measures correlation. *Frontiers in Psychology*, 8:1–13, 2017.

[224] Hugo Cerda-Kohler, Yolanda Pullin, and Jorge Cancino-López. Effects of continuous and intermittent endurance exercise in autonomic balance, rating perceived exertion and blood lactate levels in healthy subjects. *Apunts Medicina de l'Esport*, 50(185):29–34, 2015.

[225] Barry Drust, Triston Reilly, and Nigel T. Cable. Physiological responses to laboratory-based soccer-specific intermittent and continuous exercise. *Journal of Sports Sciences*, 18(11):885–892, 2000.

[226] Renato Barroso, Ronaldo K. Cardoso, Everton Crivoi Carmo, and Valmor Tricoli. Perceived exertion in coaches and young swimmers with different training experience. *International Journal of Sports Physiology and Performance*, 9(2):212–216, 2014.

[227] Mark D. Winborn, Andrew W. Meyers, and Carol Mulling. The Effects of Gender and Experience on Perceived Exertion. *Journal of Sport and Exercise Psychology*, 10(1):22–31, 1988.

[228] Laura D. Goodwin and Nancy L. Leech. Understanding correlation. *The Journal of Experimental Education*, 74(3):251–266, 2006.

[229] Jacqueline A. Alderson, Luke S. Hopper, Bruce C. Elliott, and Timothy Ackland. Risk factors for lower back injury in male dancers performing ballet lifts. *Journal of Dance Medicine & Science*, 13(3):83–89, 2009.

[230] Travis W. Sweet, Carl Foster, Michael R. McGuigan, and Glenn Brice. Quantitation of resistance training using the session rating of perceived exertion method. *Journal of Strength and Conditioning Research*, 18(4):796–802, 2004.

[231] Annamaria Salzano, Fabiana Camuso, Mario Sepe, Maha Sellami, Luca P. Ardigò, and Johnny Padulo. Acute effect of toe cap choice on toe deviation angle and perceived pain in female professional ballet dancers. *BioMed Research International*, 2019(March), 2019.

[232] Martin A. Bahr and Roald Bahr. Jump frequency may contribute to risk of jumper's knee: a study of interindividual and sex differences in a total of 11 943 jumps video recorded during training and matches in young elite volleyball players. *British Journal of Sports Medicine*, 48(17):1322–1326, 2014.

[233] Aaron Scanlan, Ben Dascombe, and Peter Reaburn. A comparison of the activity demands of elite and sub-elite Australian men's basketball competition. *Journal of Sports Sciences*, 29(11):1153–1160, 2011.

[234] Lauren C. Benson, Oluwatoyosi B. A. Owoeye, Anu M. Räisänen, Carlyn Stilling, W. Brent Edwards, and Carolyn A. Emery. Magnitude, Frequency, and Accumulation: Workload Among Injured and Uninjured Youth Basketball Players. *Frontiers in Sports and Active Living*, 3(April):1–18, 2021.

[235] Gabriel J. Sanders, Brian Boos, and Frank Shipley. An Accelerometer-Based Training Load Analysis to Assess Volleyball An Accelerometer-Based Training Load Analysis to Assess Volleyball Performance. *Journal of Exercise and Nutrition*, 1(1):3–8, 2018.

[236] Thomas Jaitner, Georg Ebker, and Marcus Schmidt. Estimation of the Jump Height for the Volleyball Spike By a Mobile Imu Unit. In *35th Conference of the International Society of Biomechanics in Sports*, number 1, pages 222–225, 2017.

[237] Kerry MacDonald, Roald Bahr, Jennifer Baltich, Jackie L. Whittaker, and Willem H. Meeuwisse. Validation of an inertial measurement unit for the measurement of jump count and height. *Physical Therapy in Sport*, 25:15–19, 2017.

[238] Christopher M. Skazalski, Rod Whiteley, Clint Hansen, and Roald Bahr. A valid and reliable method to measure jump-specific training and competition load in elite volleyball players. *Scandinavian Journal of Medicine & Science in Sports*, 28(5):1579–1585, 2018.

[239] Tony Monnet, Arnaud Decatoire, and Patrick Lacouture. Comparison of algorithms to determine jump height and flight time from body mounted accelerometers. *Sports Engineering*, 17(4):249–259, 2014.

[240] Gavin L. Moir. Three different methods of calculating vertical jump height from force platform data in men and women. *Measurement in Physical Education and Exercise Science*, 12(4):207–218, 2008.

[241] Fazle Sadi and Richard Klukas. Reliable jump detection for snow sports with low-cost mems inertial sensors. *Sports Technology*, 4(1-2):88–105, 2011.

[242] Antonio García-de Alcaraz, Rodrigo Ramírez-Campillo, Miguel Rivera-Rodríguez, and Blanca Romero-Moraleda. Analysis of jump load during a volleyball season in terms of player role. *Journal of Science and Medicine in Sport*, 23(10):973–978, 2020.

[243] Matt Taberner, Tom Allen, and Daniel Dylan Cohen. Progressing rehabilitation after injury: Consider the 'control-chaos continuum'. *British Journal of Sports Medicine*, 54(2):116–117, 2020.

[244] Bill Allerheiligen and Robb Rogers. Plyometrics Program Design. *Strength and Conditioning Journal*, 17(4):26–31, 1995.

[245] Jasper Verheul, Niels J. Nedergaard, Jos Vanrenterghem, and Mark A. Robinson. Measuring biomechanical loads in team sports – from lab to field. *Science and Medicine in Football*, 4(3):246–52, 2020.

[246] Roald Bahr and I.A. Bahr. Incidence of acute volleyball injuries: A prospective cohort study of injury mechanisms and risk factors. *Scandinavian Journal of Medicine and Science in Sports*, 7(3):166–171, 1997.

[247] Laurel A. Borowski, Ellen E. Yard, Sarah K. Fields, and R. Dawn Comstock. The epidemiology of US high school basketball injuries, 2005-2007. *American Journal of Sports Medicine*, 36(12):2328–2335, 2008.

[248] Rhiannon Campbell, David Pease, and Phillip Cossens. Quantifying landing impacts during a leg strength circuit in male artistic gymnasts - a pilot study. *36th Conference of the International Society of Biomechanics in Sports*, 36(1):831–834, 2018.

[249] Julie P. Burland, Jereme B. Outerleys, Christian Lattermann, and Irene S. Davis. Reliability of wearable sensors to assess impact metrics during sport-specific tasks. *Journal of Sports Sciences*, 39(4):406–411, 2021.

[250] Andrew D. Vigotsky, Karl E. Zelik, J. Lake, and Richard N. Hinrichs. Mechanical misconceptions: Have we lost the "mechanics" in "sports biomechanics"? *Journal of Biomechanics*, 93(May):1–5, 2019.

[251] Daniel J. Cleather and Anthony M.J. Bull. The development of a segment-based musculoskeletal model of the lower limb: Introducing FREEBODY. *Royal Society Open Science*, 2(6), 2015.

[252] John R. Harry, Jarrod Blinch, Leland A. Barker, John Krzyszkowski, and Luke Chowning. Low-Pass Filter Effects on Metrics of Countermovement Vertical Jump Performance. *Journal of Strength and Conditioning Research*, Publish Ahead of Print, 2020.

[253] Steven T. McCaw, Jacob K. Gardner, Lindsay N. Stafford, and Michael R. Torry. Filtering ground reaction force data affects the calculation and interpretation of joint kinetics and energetics during drop landings. *Journal of Applied Biomechanics*, 29(6):804–809, 2013.

[254] Ryan S. Alcantara, W. Brent Edwards, Guillaume Y. Millet, and Alena M. Grabowski. Predicting continuous ground reaction forces from accelerometers during uphill and downhill running: a recurrent neural network solution. *PeerJ*, 10(e12752):1–21, 2022.

[255] Zijun Zhang. Improved Adam Optimizer for Deep Neural Networks. In *2018 IEEE/ACM 26th International Symposium on Quality of Service (IWQoS)*, pages 1–2, 2018.

[256] Kelly R. Sheerin, Duncan Reid, and Thor F. Besier. The measurement of tibial acceleration in runners—A review of the factors that can affect tibial acceleration during running and evidence-based guidelines for its use. *Gait and Posture*, 67:12–24, 2019.

[257] Daniel T.P. Fong, Yue-Yan Chan, Youlian Hong, Patrick S.H. Yung, Kwai-Yau Fung, and Kai-Ming Chan. Estimating the complete ground reaction forces with pressure insoles in walking. *Journal of Biomechanics*, 41(11):2597–601, 2008.

[258] Alok Kumar Chowdhury, Dian Tjondronegoro, Vinod Chandran, and Stewart Trost. Ensemble methods for classification of physical activities from wrist ac- celerometry. *Medicine & Science in Sports & Exercise*, 49(9), 2017.

[259] Ye Ren, Le Zhang, and P.N. Suganthan. Ensemble Classification and Regression-Recent Developments, Applications and Future Directions. *IEEE Computational Intelligence Magazine*, 11(1):41–53, 2016.

[260] Cheng K. Li Jundong, Wang S., Morstatter F., Trevino R.P., Tang J., and Liu H. Feature selection: A Data Perspective. *ACM Computing Surveys*, 50(6):1–45, 2015.

[261] Adam D. Sylvester, Steven G. Lautzenheiser, and Patricia Ann Kramer. A review of musculoskeletal modelling of human locomotion. *Interface Focus*, 11(5):1–16, 2021.

[262] Carlos D. Gómez-Carmona, José Pino-Ortega, Braulio Sánchez-Ureña, Sergio J. Ibáñez, and Daniel Rojas-Valverde. Accelerometry-based external load indicators in sport: Too many options, same practical outcome? *International Journal of Environmental Research and Public Health*, 16(24):1–13, 2019.

[263] Steve Barrett, Adrian Midgley, and Ric Lovell. PlayerLoad™: Reliability, convergent validity, and influence of unit position during treadmill running. *International Journal of Sports Physiology and Performance*, 9(6):945–952, 2014.

[264] IMeasureU. What is Impact Load? https://imeasureu.com/2020/02/26/guide-to-impact-load-imeasureus-new-workload-metric/, 2020. Date accessed: 2021-10-03.

[265] Nutrition and Athletic Performance. *Medicine and Science in Sports and Exercise*, 48(3):543–568, 2016.

[266] Mathieu Nédélec, Alan McCall, Chris Carling, Franck Legall, Serge Berthoin, and Gregory Dupont. Recovery in soccer: Part II-recovery strategies. *Sports Medicine*, 43(1):9–22, 2013.

[267] Mathieu Nédélec, Shona Halson, Barthélémy Delecroix, Abd Elbasset Abaidia, Said Ahmaidi, and Gregory Dupont. Sleep Hygiene and Recovery Strategies in Elite Soccer Players. *Sports Medicine*, 45(11):1547–1559, 2015.

[268] Robin T. Thorpe, Greg Atkinson, Barry Drust, and Warren Gregson. Monitoring fatigue status in elite team-sport athletes: Implications for practice. *International Journal of Sports Physiology and Performance*, 12:27–34, 2017.

APPENDIX A

Ethical Approval for Chapters 3 and 4

Reference: SMEC_2019-20_033

Name of proposer(s)	Adam Mattiussi Joseph Shaw
Name of supervisor	Jamie Tallent Phil Price Charlie Pedlar Matt Springham
Programme of study	PhD
Title of project	Injury Surveillance and Rehearsal Workload of a Professional Classical Ballet Company Over 5 Seasons

Supervisors, please complete section 1. If approved at level 1, please forward a copy of this Approval Sheet to the Faculty Ethics Representative for their records.

SECTION 1: To be completed by supervisor.			
☐ Approved at Level 1. ☒ Refer to Faculty Ethics Representative for consideration at Level 2 or Level 3.			
Signature of Supervisor (for student research projects):		Date:	28/08/2020

SECTION 2: To be completed by Faculty Ethics Representative.			
☒ Approved at Level 2. ☐ Level 3 consideration is required by Ethics Sub-Committee.			
Signature of Faculty Ethics Representative:		Date:	01/09/2020

APPENDIX B

Ethical Approval for Chapters 6 and 7

Reference: SMEC_2018-19_060

Name of proposer(s)	Joseph Shaw
Name of supervisor	Dr Charles Pedlar
Programme of study	PhD
Title of project	Quantifying Workload in Elite Ballet Dancers

Supervisors, please complete section 1. If approved at level 1, please forward a copy of this Approval Sheet to the Faculty Ethics Representative for their records.

SECTION 1: To be completed by supervisor.			
☐ Approved at Level 1. X - Refer to Faculty Ethics Representative for consideration at Level 2.			
Signature of Supervisor (for student research projects):		Date:	09/01/2019

SECTION 2: To be completed by Faculty Ethics Representative.			
X - Approved at Level 2. ☐ Level 3 consideration is required by Ethics Sub-Committee.			
Signature of Faculty Ethics Representative:		Date:	28.02.19

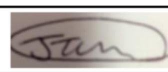
APPENDIX C

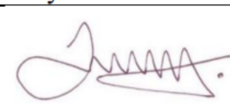
Ethical Approval for Chapter 8

Reference: SMU_ETHICS_2020-21_151

Name of proposer(s)	Adam Mattiussi Joseph Shaw
Name of supervisor	Jamie Tallent Phil Price Charlie Pedlar Matt Springham
Programme of study	PhD
Title of project	Kinetics and kinematics during jumping in professional ballet dancers

Supervisors, please complete section 1. If approved at level 1, please forward a copy of this Approval Sheet to the Faculty Ethics Representative for their records.

SECTION 1: To be completed by supervisor.			
☐ Approved at Level 1. ☒ Refer to Faculty Ethics Representative for consideration at Level 2 or Level 3.			
Signature of Supervisor (for student research projects):		Date:	25/09/20

SECTION 2: To be completed by Faculty Ethics Representative.			
☒ Approved at Level 2. ☐ Level 3 consideration is required by Ethics Sub-Committee.			
Signature of Faculty Ethics Representative:		Date:	3 February 2021

APPENDIX D

Included and excluded subject areas in the searches of Web of Science and ProQuest

D.1 Web of Science

D.1.1 Included

Sport Sciences, Nutrition Dietetics, Dance, Rehabilitation, Neurosciences, Music, Public Environmental Occupational Health, Engineering Biomedical, Medicine General Internal, Physics Applied, Hospitality Leisure Sport Tourism, Psychology, Social Sciences Biomedical, Multidisciplinary Sciences, Surgery, Theater, Biochemistry Molecular Biology, Physiology, Psychology Biological, Medicine Research Experimental, Physics Multidisciplinary, Biology, Biophysics, Endocrinology Metabolism, Health Care Sciences Services, Primary Health Care, Orthopedics.

D.1.2 Excluded

Communication, Psychology Social, Computer Science, Software Engineering, Cultural Studies, Computer Science Theory Methods, Literature, Criminology Penology, Area Studies, Economics, Education Scientific Disciplines, Education Educational Research, Environmental Sciences, Environmental Studies, , Geography, Evolutionary Biology, Management, Women's Studies, Astronomy Astrophysics, Psychology Experimental, Radiology Nuclear Medicine Medical Imaging, Cell Biology, Psychology Multidisciplinary, Religion, Law, Asian Studies, Business, Family Studies, Humanities Multidisciplinary, Engineering Electrical Electronic, Physics Nuclear, Anthropology, Entomology, Art, Chemistry Physical, Sociology, Computer Science Artificial Intelligence, Film Radio Television, Behavioral Sciences, Oncology, Genetics Heredity, Geriatrics Gerontology, Psychology Developmental, Computer Science Cybernetics, Social Sciences Interdisciplinary, Substance Abuse, Linguistics, Zoology, Political Science, Psychology Clinical, Computer Science Information Systems, Social Issues, Ecology, Integrative Complementary Medicine, Urban Studies, History, Obstetrics Gynecology, Biotechnology Applied Microbiology, Gerontology, Health Policy Services, Materials Science Multidisciplinary, Psychology Applied, Philosophy, Pharmacology

Pharmacy, Rheumatology, Engineering Mechanical, Pediatrics, Computer Science Interdisciplinary Applications, Instruments Instrumentation, Psychiatry, Clinical Neurology, Language Linguistics, Robotics.

D.2 ProQuest

D.2.1 Included

Theater, Studies, Dance, Humans, Research, Dancers & Choreographers, Experiments, Hypotheses, Researchers

D.2.2 Excluded

Politics, Poetry, Literary Criticism, Art, Motion Pictures, Music, Books, Novels, Culture, Women, Drama, Writers, Philosophy, Musicians & Conductors, Actors, Musical Performances, Motion Picture Directors & Producers, Audience, History, Religion, Aesthetics, Essays, Feminism, Animals, Narratives, Reading, Poets, Linguistics, Writing, Creativity, African Americans, Cultural Identity, Male, Female, Literature, Audiences, Fiction, Ideology, Gender, Theory, Language, Society, Opera, Sexuality, Children, Females, Traditions, Collaboration, Films, Animal Behavior, Behavior, Ethics, Semantics, Brain, Consciousness, Composers, 20th Century, Violence, Christianity, Cognition & Reasoning, Algorithms, Adult, 19th Century, Metaphor, Motion Picture Criticism, War, Archives & Records, Modernism, Historical Text Analysis, Memory, Neurosciences, Proteins, Bees, Emotions, English, Sound, Artists, Painting, Computer Simulation, French Language, Popular Music, Self Concept, Spirituality, Postmodernism, Race, Communication, Psychology, Television, Semiotics, 18th Century, Social Networks.

APPENDIX E

Supplementary Files

These files can be accessed via the following url:
https://github.com/joseph-shaw/PhD/tree/main/Supplementary%20Files

Rehearsal Characteriststics.xlsx
Rehearsal characteristics for Royal Ballet productions discussed in Chapter 5.

Jump Load Function.R
Code for creating a function to calculate jump frequency and height from accelerometer data, detailed in Chapter 7.

Jump Load Spreadsheeet.xlsm
A spreadsheet containing the algorithm to calculate jump frequency and height from accelerometer data, detailed in Chapter 7.

Neural Network - LOSOCV.R
Code to reproduce the leave-one-subject-out cross validation detailed in Chapter 8.

Neural Network - All Data.R
Code to build the neural networks detailed in Chapter 8 from all participant data.

p01_data.csv – p06_data.csv
Data collected in Chapter 8, processed by 'Neural Network - LOSOCV.R' and 'Neural Network - All Data.R'

OpenTrack Installation.R
A script that installs OpenTrack.